MICHIGAN STREAM SALMONID GROWTH AND SURVIVAL IN A CHANGING CLIMATE: PREDICTIONS AND IMPLICATIONS FOR RESILIENCE-BASED MANAGEMENT

By

Andrew Kenneth Carlson

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ABSTRACT

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From biodiversity and aesthetic beauty to recreation and water for human use (e.g., municipal, industrial, agricultural), streams and rivers are socioeconomically and ecologically vital ecosystems. Coldwater streams and their biota are particularly unique, but they are increasingly threatened by climate change and associated temperature warming, changing hydrology (e.g., groundwater input, temperature; precipitation magnitude, intensity, frequency), and modifications to thermal and physical habitats that support aquatic organism growth, reproduction, and survival. As such, monitoring and modeling of stream thermal-hydrological regimes are important for sustainable management of coldwater fishes – including Brook Trout (*Salvelinus fontinalis*), Brown Trout (*Salmo trutta*), and Rainbow Trout (*Oncorhynchus mykiss*) – in a changing climate. Ultimately, stream salmonid management decisions should foster social-ecological resilience – the ability to retain robust stream ecosystems and human systems amid stressors such as climate change – and promote resilience-based management. Using Michigan trout streams as a case study, the objectives of this dissertation were to:

- Develop stream-specific temperature models to forecast stream thermal regimes and project thermal habitat suitability for Brook Trout, Brown Trout, and Rainbow Trout growth and survival throughout Michigan amid climate change;
- 2) Compare stream-specific and generalized (i.e., region-specific) temperature models relative to their accuracy (i.e., exactness of temperature prediction) and efficiency (i.e.,

applicability at management-relevant spatial extents) to develop a model implementation and evaluation approach that can be used for salmonid management programs in Michigan and beyond;

- 3) Integrate stream temperature modeling results with other thermal habitat information (e.g., groundwater input, watershed and riparian land use/land cover) and trout relative abundance to create a decision-support tool to assist fisheries professionals in operationalizing resilience-based salmonid management within and beyond Michigan in a changing climate;
- Develop an approach for incorporating precipitation and groundwater into stream temperature modeling and thermal habitat management amid climate change.

Climate change will affect Michigan stream trout in ways that vary among streams and populations. In most groundwater-dominated streams, thermal habitats can be accurately modeled and effectively managed using a generalized (i.e., region-specific) approach. However, stream-specific temperature modeling is considerably more accurate than a generalized approach in surface runoff-dominated systems, where the increased resource expenditure (e.g., money, time, personnel) associated with stream-specific modeling may be justified in systems containing high-priority fisheries resources (e.g. trophy individuals, endangered species). Decision-support tools are valuable for synthesizing biological, hydrological, and thermal data in ways that foster informed management decision-making on local and regional scales. Similarly, developing precipitation- and groundwater-corrected stream temperature models is important for accurate, efficient thermal habitat projections that promote resilience-based salmonid management in a changing climate. To Mom and Dad, for guidance, patience, and unwavering love

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INTRODUCTION

Streams and rivers are "arteries" of the landscape that transport water from land to lakes and oceans and in the process provide important ecological goods and services to humanity (e.g., recreation; water for municipal, industrial, and agricultural use; Loomis et al. 2000). However, stressors such as climate change, invasive species introductions, land-use alterations, and habitat fragmentation (e.g., dam installation) are threatening riverine ecosystems across the globe (Dudgeon et al. 2006, Reid et al. 2018). As these stressors continue to alter water availability, water quality, and related ecosystem structure and function in streams and rivers, aquatic and fisheries managers have started to embrace resilience as a guiding principle for maintaining and enhancing aquatic ecosystem conservation (Hansen et al. 2015). Resilience is the capacity of a system to withstand disturbance and thereby retain its structure and function (Holling 1973) and continue to provide benefits desired by humans. Currently, climate change is particularly threatening to the resilience of streams and rivers worldwide as it increases air and water temperature and alters local and regional hydrology (e.g., increased groundwater temperature, more or less frequent precipitation), often reducing the availability and quality of physical, chemical, and thermal habitats for aquatic organisms (Woodward et al. 2010; Snyder et al. 2015).

Brook Trout (*Salvelinus fontinalis*), Brown Trout (*Salmo trutta*), and Rainbow Trout (*Oncorhynchus mykiss*) are icons of coldwater streams and excellent indicator species for evaluating the effects of climate change on coldwater stream fisheries. Short- and long-term changes in climate that increase stream temperatures can negatively affect the growth, reproduction, survival, and population resilience of these salmonids and other coldwater fishes – those with temperature preferenda $\leq 20^{\circ}$ C (Raleigh 1982a, b; Raleigh et al. 1986; Lyons et al. 2009; Dunham et al. 2009). Hence, it is important to predict the impacts of climate change on coldwater streams and their fisheries to maintain healthy coldwater ecosystems and associated

ecological services (e.g., recreational fishing, flood control) locally, regionally, and globally. An effective way to project climate change effects on fish growth, reproduction, survival, and population resilience is to develop models that predict stream temperatures as a function of changing climatic, hydrological, and landscape variables (e.g., air temperature, precipitation, groundwater, riparian/watershed land cover). Stream temperature predictions can then be integrated with other local and regional data (e.g., fish abundance, growth) to develop informed strategies for groundwater conservation, riparian habitat protection/rehabilitation, and other trout management activities to increase the resilience of coldwater streams and trout fisheries that would otherwise be vulnerable to thermal warming.

Sustaining coldwater streams and salmonid fisheries in a changing climate requires management and governance programs that promote thermal resilience (i.e., ability of coldwater streams to absorb thermal changes and retain their original thermal regimes). In turn, thermal resilience promotes social-ecological resilience (i.e., ability of salmonid management programs to retain the structure and function of coldwater ecosystems and human systems amid change). By focusing on thermal resilience and social-ecological resilience, fisheries and aquatic resource professionals can implement resilience-based salmonid management: maintaining and enhancing the structure and function of coldwater stream ecosystems and allied human systems via collaborations among aquatic and terrestrial scientists, managers, policymakers, and public and private stakeholders. For example, fisheries professionals can promote resilience-based salmonid management by protecting and rehabilitating riparian zones to ensure that they have abundant trees, shrubs, grasses, and wildflowers in streams and rivers containing coldwater species projected to be negatively affected by climate change. Such riparian habitat management can greatly increase the thermal resilience of coldwater streams, thereby maintaining and enhancing

the growth, reproduction, and survival of coldwater fishes (Waco & Taylor 2010). In addition, fisheries professionals can promote resilience-based salmonid management by developing outreach and education programs to redefine stakeholder perceptions of "successful" angling and other forms of freshwater recreation in ways that extend beyond single species or groups (e.g., coldwater fishes) to encompass entire fish communities and ecosystem services (Paukert et al. 2016). Such programs can promote resilience-based salmonid management by increasing stakeholder adaptiveness in a changing climate and thereby enhancing social-ecological resilience, allowing fisheries and aquatic resource managers to focus their limited resources (e.g., time, money) on conserving the highest-priority coldwater streams and trout populations.

The goal of this dissertation is to forecast the effects of climate change on coldwater streams and trout populations in Michigan to provide fisheries professionals with a knowledge base for implementing resilience-based salmonid management programs. In particular, there is a need to develop stream temperature monitoring and modeling approaches that enable fisheries professionals to understand and predict thermal habitat conditions for trout growth and survival now and in the future. In turn, fisheries professionals need to be able to use this information in a decision-support framework, laying a foundation for resilience-based salmonid management in Michigan and throughout the United States and the world. Brook Trout, Brown Trout, and Rainbow Trout are distributed throughout more than 12,000 miles of designated coldwater trout streams in Michigan, supporting socioeconomically valuable recreational fisheries in which more than 585,000 anglers spent 8.2 million angling days in 2011 (Godby et al. 2007; USFWS 2011; MLSA 2018). In addition to the numerical abundance, wide geographic distribution, and socioeconomic importance of Michigan stream trout fisheries, coldwater stream temperatures have been monitored for long time periods (i.e., 10–20 years), making Michigan an ideal study

area for investigating how thermal warming will impact coldwater streams and trout populations. However, climate change is projected to increase stream temperatures in Michigan and other Midwestern United States by 0.8–4.0 °C (Pilgrim et al. 1998; Lyons et al. 2010). This will likely cause some streams to exceed thermal optima for Brook Trout, Brown Trout, or Rainbow Trout, causing declines in growth, reproduction, and survival, particularly during the warmest period of the year (i.e., July; Zorn et al. 2011). Hence, the need for science-driven, resilience-based salmonid management has never been greater. Such a management program requires the following (i.e., objectives of this dissertation): 1) predicting future stream temperatures and trout thermal habitat conditions; 2) comparing the advantages and disadvantages of different stream temperature projection models; and, 3) using stream temperature predictions in combination with hydrological, biological (i.e., trout population), and human dimensions data to make informed, resilience-based salmonid management decisions.

The four chapters of this dissertation address the objectives described above. In collaboration with the Michigan Department of Natural Resources (MDNR), I selected Michigan coldwater streams that spanned a thermal gradient from north to south and a hydrological gradient from surface runoff to groundwater dominance so that my study systems encompassed the diversity of thermal and hydrological conditions experienced by Michigan stream trout. In addition, all streams were important from a fisheries management standpoint as they supported the wild production of, and recreational fisheries for, Brook Trout, Brown Trout, Rainbow Trout, or a combination of these species. In these streams, I measured hourly temperatures from late May through mid-October for three years (2016-2018) and developed stream-specific temperature models to forecast trout thermal habitat suitability until 2056 in a changing climate

(Chapter 1), with the goal of enabling fisheries professionals to anticipate future thermal habitat conditions and thereby create resilience-based salmonid management programs. Although stream-specific temperature models account for the unique factors that regulate each stream's thermal regime (e.g., solar radiation, groundwater input), they are not always possible to use amid limitations in management resources (e.g., time, money, personnel). Hence, I developed generalized (i.e., region-specific) temperature models, compared them to stream-specific models with respect to accuracy (i.e., exactness of temperature prediction) and efficiency (i.e., applicability at management-relevant spatial extents), and made recommendations for trout thermal habitat monitoring and management (Chapter 2). In conducting research for Chapters 1 and 2 and interacting with the MDNR and the United States Geological Survey (USGS), I came to understand that when managing stream trout populations, fisheries professionals must integrate diverse sources of information, including stream temperatures, the factors that influence those temperatures (e.g., stream hydrology, riparian and watershed land cover), and trout population parameters (e.g., fish abundance, growth) while considering the perspectives and needs of fisheries stakeholders (e.g., policy makers, anglers, general public). To help facilitate this process, I designed and implemented a decision-support tool based on a formal survey of MDNR fisheries professionals regarding their opinions on and attitudes toward trout management in Michigan given a changing climate (Chapter 3). The decision-support tool synthesized stream temperature projections with other trout management decision-making criteria (e.g., groundwater input, riparian and watershed land cover, trout relative abundance) to prioritize streams for resilience-based salmonid management in a changing climate (Rohweder et al. 2015a,b). Finally, recognizing that projected changes in climate could significantly impact trout thermal habitat quality and quantity via changes to precipitation and groundwater regimes

(generally not incorporated into stream temperature models), I developed an approach for predicting the effects of changing precipitation and groundwater on growth and survival of Brook Trout, Brown Trout, and Rainbow Trout (Chapter 4). In particular, I evaluated the accuracy and efficiency of precipitation- and groundwater-corrected stream temperature models relative to conventional air-stream temperature models to determine if fisheries professionals would benefit from monitoring and modeling precipitation and groundwater in their trout management programs.

This research suggests that climate change will affect Michigan stream trout populations in ways that are expected (e.g., direct stream temperature warming) and ways that are less anticipated (e.g., changes in precipitation and groundwater dynamics). Whereas the thermal habitat suitability of some systems for trout growth and survival will decline from present and historical levels, thermal habitats will likely become more suitable in other streams. Overall, Michigan streams and trout populations are changing and will continue to change (Carlson et al. 2017a, b; Carlson et al. 2018; Zorn et al. 2018). This dissertation provides fisheries professionals and allied stakeholders throughout Michigan, the United States, and the world with a knowledge base to address these changes via stream temperature monitoring and modeling approaches and decision-support tools. In turn, these approaches and tools are the raw material for resiliencebased salmonid management that maintains and enhances the structure and function of coldwater stream ecosystems and allied human systems via collaborations among aquatic and terrestrial scientists, managers, policymakers, and public and private stakeholders.

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CHAPTER 1: PROJECTED IMPACTS OF CLIMATE CHANGE ON STREAM SALMONIDS WITH IMPLICATIONS FOR RESILIENCE-BASED MANAGEMENT

Carlson, A. K., W. W. Taylor, K. M. Schlee, T. G. Zorn, and D. M. Infante. 2017. Projected impacts of climate change on stream salmonids with implications for resilience-based management. Ecology of Freshwater Fish 26:190–204.

The content of this chapter is intended to be identical to the published manuscript cited above and reflects specifications (e.g., formatting) for *Ecology of Freshwater Fish*. Any differences should be minor and are unintended.

Abstract

The sustainability of freshwater fisheries is increasingly affected by climate warming, habitat alteration, invasive species, and other drivers of global change. The State of Michigan, USA, contains ecologically, socioeconomically valuable coldwater stream salmonid fisheries that are highly susceptible to these ecological alterations. Thus, there is a need for future management approaches that promote resilient stream ecosystems that absorb change amidst disturbances. Fisheries professionals in Michigan are responding to this need by designing a comprehensive management plan for stream brook charr (Salvelinus fontinalis), brown trout (Salmo trutta), and rainbow trout (Oncorhynchus mykiss) populations. To assist in developing such a plan, we used stream-specific regression models to forecast thermal habitat suitability in streams throughout Michigan from 2006–2056 under different predicted climate change scenarios. As baseflow index (i.e., relative groundwater input) increased, stream thermal sensitivity (i.e., relative susceptibility to temperature change) decreased. Thus, the magnitude of temperature warming and frequency of thermal habitat degradation were lowest in streams with the highest baseflow indices. Thermal habitats were most suitable in rainbow trout streams as this species has a wider temperature range for growth (12.0–22.5°C) compared to brook charr (11.0–20.5°C) and brown trout (12.0–20.0°C). Our study promotes resilience-based salmonid management by providing a methodology for stream temperature and thermal habitat suitability prediction. Fisheries professionals can use this approach to protect coldwater habitats and drivers of stream cooling and ultimately conserve resilient salmonid populations amidst global change.

KEYWORDS: brook charr, brown trout, rainbow trout, Michigan, temperature, resilience

Introduction

As climate warming, habitat fragmentation, invasive species, and other drivers of global change alter aquatic ecosystems throughout the world, managing fisheries for resilience has become an important conservation framework (Hansen et al. 2015). Resilience is the capacity of a system to absorb disturbances and retain its structure and function (Holling 1973). Managing aquatic ecosystems for resilience is particularly important when they contain species that are sensitive to ecological stressors. For instance, with relatively low thermal tolerance thresholds (Raleigh 1982a,b; Raleigh et al. 1986), salmonid fishes may experience reductions in growth and survival due to temperature elevation caused by climate change. Thus, managing these species and their ecosystems for thermal resilience is an important task. Collaboration among scientists, managers, policy makers, and public stakeholders will be important for developing management approaches commensurate with the wide geographic distribution and high socioeconomic value of salmonid populations (Isaak et al. 2015; Snyder et al. 2015).

Temperature exerts a fundamental physiological influence on fish metabolism, which regulates growth, survival, and reproduction of individuals (Dodds and Whiles 2010) and ultimately the dynamics of populations and communities. For example, water temperature is an important factor determining fish distribution and assemblage composition (Magnuson et al. 1979). Temperatures above species-specific thermal maxima cause mortality; temperatures below maxima alter fish growth, reproduction, abundance, and population size structure (Magnuson et al. 1997). In addition, thermal warming can indirectly decrease fish growth and survival by degrading water quality (e.g., reduced dissolved oxygen; Ficklin et al. 2013).

Climate change is predicted to increase stream temperatures and thereby alter thermal habitat suitability (Lyons et al. 2010) and fish community composition (Isaak et al. 2012).

Moreover, dams, culverts, and other anthropogenic barriers increase water temperatures and decrease population and habitat connectivity (Lessard 2000; Hayes et al. 2006). Regardless of mechanism, stream salmonids are sensitive to thermal warming because they are adapted to cold and coolwater environments (Raleigh 1982a,b; Raleigh et al. 1986; Wehrly et al. 2007). Climate-driven increases in water temperature may reduce salmonid growth, reproduction, and survival in streams currently near thermal optima. Thus, it is imperative that fisheries professionals develop management strategies to promote thermal resilience and thereby conserve salmonid populations in a warming climate.

The State of Michigan, USA, has ecologically and socioeconomically valuable populations of brook charr (*Salvelinus fontinalis*), brown trout (*Salmo trutta*), and rainbow trout (*Oncorhynchus mykiss*) distributed throughout 31,000 km of streams (Godby et al. 2007; Tyler and Rutherford 2007). Projected air temperature warming resulting from climate change is predicted to increase stream temperatures in the Midwestern United States by 0.8–4.0°C (Pilgrim et al. 1998; Lyons et al. 2010). If temperatures exceed thermal optima for these species, growth, reproduction, and/or survival will decline, particularly during the warmest month of the year (i.e., July; Zorn et al. 2011). Thus, Michigan is an ideal study area for investigating how thermal warming will impact coldwater streams and salmonid population dynamics. This information will enable fisheries professionals to develop resilience-based management programs: collaborative efforts among scientists, managers, policy makers, and public stakeholders to maintain stream ecosystem structure and function amidst global change.

The goal of this study was to evaluate effects of projected air temperature warming on salmonid thermal habitat suitability in coldwater streams in Michigan to facilitate development of a resilience-based salmonid management program. Our first objective was to measure the

accuracy of stream-specific air-water temperature regression models by backcasting stream temperatures in 2006 and 2012, years with pre-existing air and stream temperature metrics. Our second objective was to forecast stream temperatures in 2036 and 2056 and project thermal habitat suitability for brook charr, brown trout, and rainbow trout growth and survival. We predicted that water temperatures would increase overall from 2006–2056 but unevenly among streams and time periods (e.g., 2012–2036, 2036–2056) due to system-specific patterns of thermal warming and temporal variability in projected carbon dioxide (CO₂) emissions (Arblaster et al. 2014). We expected that thermal habitat impairment would occur more frequently in streams with extensive surface runoff than in groundwater-dominated, thermally buffered systems (Sear et al. 1999; Krider et al. 2013).

Methods

Study area

Our study encompassed 30 coldwater streams throughout the State of Michigan, USA (Figure 1.1). Streams were chosen in three Michigan Department of Natural Resources (MDNR) management regions (i.e., Upper Peninsula [UP], northern Lower Peninsula [NLP], and southern Lower Peninsula [SLP]; Table 1.1) to conduct the study at a statewide scale relevant for salmonid management that also spanned a latitudinal thermal gradient in which temperatures increased from north (47.03°N) to south (42.64°N). In addition, streams were selected to encompass a hydrological gradient from surface-runoff to groundwater dominance by evaluating their relative base flow, the component of streamflow attributable to groundwater. We obtained each stream's base flow index (BFI), the mean rate of base flow divided by the corresponding mean rate of total streamflow, using a United States Geological Survey report (Neff et al. 2005).

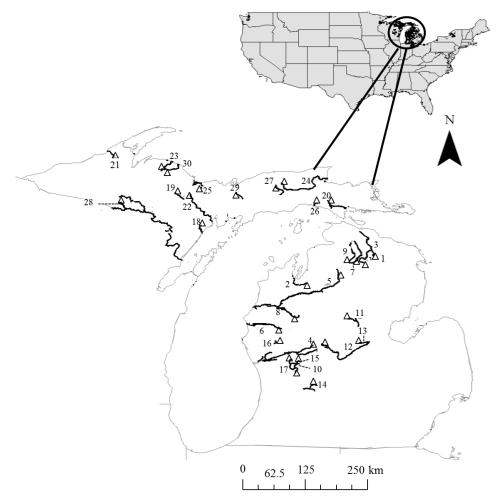


FIGURE 1.1. Map of brook charr, brown trout, and rainbow trout streams used for air-stream temperature modeling in Michigan, USA. Streams and corresponding identification numbers are listed in Table 1.1. Triangles denote locations of MDNR stream temperature gauges.

TABLE 1.1. Descriptive information about 30 salmonid streams used for temperature modeling in Michigan, USA. Region refers to Michigan location (i.e., Upper Peninsula [UP], northern Lower Peninsula [NLP], southern Lower Peninsula [SLP]). Subbasin denotes the National Hydrography Dataset subbasin (i.e., 8-digit Hydrologic Unit Code). Map number refers to stream identifiers in Figure 1.1. Species refers to salmonids present in each stream (i.e., brook charr [BKC], brown trout [BNT], rainbow trout [RBT]). BFI denotes baseflow index, the mean rate of base flow divided by the corresponding mean rate of total streamflow (Neff et al. 2005).

Stream	Region	Sub-basin	Map number	Species	BFI
Bark River	UP	Cedar-Ford	18	BNT	0.60
Bear Creek	SLP	Kalamazoo	14	BNT	0.58
Black River	NLP	Black	1	BKT	0.63
Boardman River	NLP	Boardman-Charlevoix	2	BKT, BNT	0.58
Bryan Creek	UP	Escanaba	19	BKT	0.62
Canada Creek	NLP	Black	3	BKT	0.63
Carp River	UP	Carp-Pine	20	BKT, BNT, RBT	0.64
Cedar Creek	SLP	Lower Grand	10	BKT, BNT	0.50
Cedar River	SLP	Cedar-Ford	11	BNT	0.60
Chocolay River	UP	Betsy-Chocolay	25	RBT	0.62
Davenport Creek	UP	Brevoort-Millecoquins	26	RBT	0.65
Duke Creek	SLP	Lower Grand	15	BKT, BNT	0.50
East Branch Fox River	UP	Manistique	27	BKT, BNT	0.73
Elm River	UP	Keweenaw Peninsula	21	RBT	0.45
Escanaba River	UP	Escanaba	22	BKT, BNT	0.44
Iron River	UP	Brule	28	BKT	0.59
Little Indian River	UP	Manistique	29	BKT	0.73
Little Muskegon River	NLP	Muskegon	4	RBT	0.62
Manistee River	NLP	Manistee	5	BKT, BNT, RBT	0.65

TABLE 1.1 (cont'd).

Stream	Region	Sub-basin	Map number	Species	BFI
Martin Creek	SLP	Pere Marquette-White	16	BKT	0.61
Pere Marquette River	NLP	Pere Marquette-White	6	BNT	0.61
Pigeon River	NLP	Cheboygan	7	BNT, RBT	0.65
Pine River	SLP	Pine	12	BNT	0.65
Pine River	NLP	Manistee	8	BKT, BNT, RBT	0.49
Prairie Creek	SLP	Lower Grand	13	BNT	0.50
Rogue River	SLP	Lower Grand	17	BNT, RBT	0.50
Salmon Trout River	UP	Keweenaw Peninsula	23	BKT	0.45
Tahquamenon River	UP	Tahquamenon	24	BNT	0.55
West Branch Sturgeon River	NLP	Cheboygan	9	BKT, BNT, RBT	0.65
Yellow Dog River	UP	Dead-Kelsey	30	RBT	0.52

Baseflow index ranges from zero to one with increasing groundwater input (Wahl and Wahl 1988); streams in our study ranged from 0.44–0.73 (Table 1.1). All BFI calculations were made using a digital filter hydrograph separation technique (Arnold and Allen 1999, Kelleher et al. 2012) whereby daily streamflow records were partitioned into groundwater and surface-runoff components. Moreover, all streams were important from a management standpoint as they supported recreational fisheries for brook charr, brown trout, rainbow trout, or a combination of these coldwater species. Only streams that had necessary historical data for development of stream-specific temperature regression models (i.e., field-measured air and water temperatures) were selected. We developed a list of streams meeting these criteria (i.e., latitudinal gradient, hydrological gradient, recreational importance, historical data) using information from the MDNR "Better Fishing Waters" webpage (MDNR 2015) and through personal communication with MDNR Fisheries Division personnel (Tracy Kolb, Todd Wills) and employees of the Michigan Council of Trout Unlimited (Trout Unlimited 2015). A minimum of five streams per region were selected for each species to ensure regional replication. One exception was the SLP, where brook charr and rainbow trout are not widely distributed and only four streams contained one or both of these species. In total, 16, 18, and 11 streams contained brook charr, brown trout, and rainbow trout, respectively. Eleven streams supported more than one species, and four supported all species (Table 1.1).

Stream-specific regression models

Historical air and water temperatures for each stream were used to create stream-specific regression models. Daily air temperatures collected in summer months (i.e., June, July, August) from 1990–2010 were compiled using the United States Historical Climate Network online

interface (http://cdiac.ornl.gov/). Air temperatures were measured at the gauging station closest to each stream's headwaters, where MDNR water temperature gauges recorded daily temperatures in summer months from 1990–2010. The most upstream gauge on each stream was selected because temperatures are typically coolest and most optimal for salmonids in headwater reaches. As such, we focused on these areas because if their thermal habitat is degraded, downstream habitat and salmonid populations will also be impaired. Hydrologic Unit Codes (HUCs) for each stream's subbasin (HUC8) and subwatershed (HUC 12) were identified using the National Hydrography Dataset Plus Version 1 (NHDPlusV1) and the Watershed Boundary Dataset (USEPA 2005). The North American Anthropogenic Barrier Dataset was used to locate and omit gauges directly below dams, which elevate temperatures compared to upstream reaches (Lessard 2000). For streams without MDNR gauges, a substitute gauge on the nearest stream within the same subwatershed was used. Stream-specific regression models were developed by pairing mean summer air and water temperatures from recent years (i.e., 2002–2010) in Microsoft Excel (Table 1.2). Air temperature coefficients represented indices of stream thermal sensitivity (i.e., relative susceptibility to temperature change; Kelleher et al. 2012) and were coupled with air temperature projections (see below) to predict future water temperatures. In addition, historical warming in each stream was evaluated by comparing air temperatures in 1976 and 2006 and multiplying this temperature change by each stream's air temperature coefficient to determine the magnitude of stream warming.

Air temperature projections

Three coupled climate models (CCMs) were used to backcast mean June, July, and August air temperatures in 2006 and 2012 and forecast mean temperatures in the same months in

Stream name	Regression	SE	F	Р	R^2
Bark R.	S = 0.32A + 12.98	0.05	49.41	< 0.01	0.86
Bear Crk.	S = 0.23A + 11.61	0.03	46.74	< 0.01	0.85
Black R.	S = 0.29A + 8.74	0.04	57.04	< 0.01	0.88
Boardman R.	S = 0.14A + 11.99	0.02	72.85	< 0.01	0.90
Bryan Crk.	S = 0.42A + 7.69	0.08	28.86	< 0.01	0.78
Canada Crk.	S = 0.60A + 6.91	0.08	61.72	< 0.01	0.88
Carp R.	S = 0.28A + 12.06	0.04	41.63	< 0.01	0.84
Cedar Crk.	S = 0.56A + 6.32	0.09	39.10	< 0.01	0.83
Cedar R. (SLP)	S = 0.25A + 11.42	0.03	97.82	< 0.01	0.92
Chocolay R.	S = 0.23A + 10.29	0.03	77.99	< 0.01	0.91
Davenport Crk.	S = 0.13A + 8.97	0.01	99.55	< 0.01	0.92
Duke Crk.	S = 0.48A + 4.45	0.08	37.27	< 0.01	0.82
E. Branch Fox R.	S = 0.33A + 7.73	0.04	86.45	< 0.01	0.91
Elm R.	S = 0.82A + 2.11	0.06	193.20	< 0.01	0.96
Escanaba R.	S = 0.88A + 3.03	0.14	39.26	< 0.01	0.83
Iron R.	S = 0.30A + 12.76	0.04	52.58	< 0.01	0.87
Little Indian R.	S = 0.06A + 14.86	0.01	83.65	< 0.01	0.91
Little Muskegon R.	S = 0.34A + 12.09	0.04	69.13	< 0.01	0.89
Manistee R.	S = 0.13A + 10.67	0.02	57.70	< 0.01	0.88
Martin Crk.	S = 0.38A + 9.61	0.05	62.93	< 0.01	0.89
Pere Marquette R.	S = 0.18A + 12.50	0.02	51.89	< 0.01	0.86
Pigeon R.	S = 0.11A + 11.93	0.01	60.49	< 0.01	0.88
Pine R. (NLP)	S = 0.22A + 10.89	0.03	73.41	< 0.01	0.90
Pine R. (SLP)	S = 0.40A + 9.23	0.04	119.15	< 0.01	0.94
Prairie Crk.	S = 0.74A + 0.95	0.07	106.03	< 0.01	0.93
Rogue R.	S = 0.23A + 13.17	0.04	27.46	< 0.01	0.77
Salmon Trout R.	S = 0.29A + 8.23	0.05	33.60	< 0.01	0.80
Tahquamenon R.	S = 0.50A + 12.29	0.05	115.88	< 0.01	0.93
W. Branch Sturgeon R.	S = 0.06A + 11.93	0.01	67.49	< 0.01	0.89
Yellow Dog R.	S = 0.38A + 9.90	0.06	45.58	< 0.01	0.85

TABLE 1.2. Stream-specific temperature regression models with standard error (SE) and coefficient of determination (R^2). *F* (i.e., $F_{1,7}$) and *P* values refer to the air temperature (A) parameter used to predict stream temperature (S). R. denotes River and Crk. denotes Creek.

2036 and 2056 for each subbasin: the Third Generation Coupled Global Climate Model (CGCM3, Canadian Centre for Climate Modelling and Analysis), the CM2 Global Coupled Climate Model (CM2, Geophysical Fluid Dynamics Laboratory at the National Oceanic and Atmospheric Administration), and the Hadley Centre Coupled Model version 3 (HadCM3, Met Office, United Kingdom's National Weather Service). All CCMs were based on the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset. Spatial downscaling was performed using the Bias-Correction Spatial Disaggregation (BCSD) approach to adjust the resolution of the climate model (~200km x 200km) to a scale germane for Michigan streams (12km x 12km; Maurer et al. 2007). The United States Forest Service's (USFS) Eastern Forest Environmental Threat Assessment Center (EFETAC) in North Carolina supplied mean June, July, and August air temperatures for Michigan subbasins containing coldwater salmonid streams. Projections were made based on the CGCM3, CM2, and HadCM3 models using area-weighted means for all years assuming the Special Report of Emission Scenarios (SRES) A2 and B1 climate forcing scenarios. The A2 scenario describes a future world with rapid economic growth and efficient energy technologies and predicts atmospheric CO_2 concentrations to be 820 ppm in 2100. In contrast, the B1 scenario projects a convergent world with a service and information economy and reduced material consumption and predicts atmospheric CO_2 concentrations 550 ppm in 2100. Combining scenarios was informative as they represent upper and lower emissions thresholds for stream temperature prediction.

Stream temperature and thermal habitat suitability projections

Stream temperatures were backcasted in 2006 and 2012 and forecasted in 2036 and 2056 by inputting CCM air temperature predictions into stream-specific regression models. Mean July

stream temperatures were projected because this month is typically the warmest and most thermally stressful for salmonids in Michigan (Zorn et al. 2011). To incorporate the range of air temperatures projected by each CCM and the intrinsic uncertainty and unique characteristics (i.e., atmospheric pressure, sea ice rheology, forest canopy density, soil layering) of each model, predictions were averaged across the three CCM's. Species-specific thermal habitat suitability status was assigned for each stream based on conditions for growth and survival associated with projected July temperatures. Status 1, 2, 3, and 4 corresponded with optimal growth, suboptimal (i.e., reduced) growth, no growth, and extirpation, respectively (Table 1.3). United States Fish and Wildlife Service (USFWS) Biological Reports (e.g., Raleigh 1982a,b; Raleigh et al. 1986) contained thermal habitat status temperature ranges for juveniles and adults of each species. Other sources (i.e., Fry et al. 1946; Baldwin 1957; Wurtsbaugh and Davis 1977; Elliott and Hurley 2000; Hay and Young 2006) contained temperature ranges for juveniles and/or adults and were used to confirm temperatures reported in the USFWS reports. When threshold temperatures (e.g., thermal minima, maxima) differed between juveniles and adults, we reported juvenile temperatures under the premise that resilient salmonid fisheries can only be conserved if young fish survive to adulthood.

Analyses

The accuracy of stream-specific regression models was evaluated by comparing each stream's projected temperature and thermal habitat suitability status in 2006 to its actual (i.e., field-measured) temperature and associated habitat status obtained from the MDNR database. The association between BFI and air temperature regression coefficients, which are indices of stream thermal sensitivity, was assessed using simple linear regression (Kelleher et al. 2012).

TABLE 1.3. Thermal habitat suitability status (Habitat status) designations and corresponding temperature ranges (Temperature) and growth conditions (Growth) for juvenile and adult brook charr (BKC; Fry et al. 1946; Baldwin 1957; Raleigh 1982a), brown trout (BNT; Raleigh et al. 1986; Elliott and Hurley 2000; Hay and Young 2006), and rainbow trout (RBT; Wurtsbaugh and Davis 1977; Raleigh 1982b).

Species	Habitat status	Temperature	Growth
BKC	1	$11.0 \le ^{\circ}C < 16.5$	Optimal
	2	$16.5 \le ^{\circ}C < 20.5$	Suboptimal
	3	$20.5 \le ^{\circ}C < 25.3$	None
	4	$^{\circ}C \ge 25.3$	Extirpation
BNT	1	$12.0 \le ^{\circ}C < 17.0$	Optimal
	2	$17.0 \le ^{\circ}C < 20.0$	Suboptimal
	3	$20.0 \le ^{\circ}C < 26.2$	None
	4	$^{\circ}C \ge 26.2$	Extirpation
RBT	1	$12.0 \le ^{\circ}C < 16.4$	Optimal
	2	$16.4 \le ^{\circ}C < 22.5$	Suboptimal
	3	$22.5 \le ^{\circ}C < 25.0$	None
	4	$^{\circ}C \ge 25.0$	Extirpation

Results

Model accuracy

Stream-specific models accurately projected temperature and thermal habitat suitability status in brook charr, brown trout, and rainbow trout streams. Under the A2 scenario, the mean deviation between predicted and actual temperatures was -0.46° C (SD = 0.56; Table 1.4). Under the B1 scenario, the mean deviation between predicted and actual temperatures was -0.58° C (SD = 0.59; Table 1.4). Under the A2 and B1 scenarios, stream-specific models predicted thermal habitat status with 93.0% percent overall accuracy in streams with brook charr (94.0% accuracy, n = 15), brown trout (89.0% accuracy, n = 16), and rainbow trout (100.0% accuracy, n = 11; Table 1.4).

Thermal habitat suitability: Brook charr

Stream-specific regression models projected that climate-induced air temperature elevation will have substantial effects on stream temperature and thermal habitat suitability, with impacts varying by BFI (i.e., streams with lower BFI were more thermally sensitive; Figure 1.2), species, region, time period, and climate forcing scenario. From 1976 to 2006, the mean temperature of brook charr streams increased by 0.74°C (Table 1.5). In the UP under the A2 and B1 scenarios, thermal habitat suitability was predicted to be optimal in the East Branch Fox and Little Indian rivers and suboptimal in the Iron River from 2006 to 2056 (Figure 1.3a,b). From 2006 to 2012, thermal habitat was projected to be optimal in Bryan Creek and the Salmon Trout River and suboptimal in the Carp and Escanaba rivers under both scenarios. From 2012 to 2036, thermal habitat was projected to become suboptimal in Bryan Creek with predicted warming by 1.19°C (A2 scenario) and 1.31°C (B1 scenario). Similarly, thermal habitat was forecasted to

TABLE 1.4. Actual versus projected stream temperatures and thermal habitat suitability (THS) status for brook charr (BKC), brown trout (BNT), and rainbow trout (RBT) as predicted by stream-specific air-water temperature regression models. Temperatures are predicted in 2006 under the A2 (820 ppm atmospheric CO₂ by 2100) and B1 (550 ppm atmospheric CO₂ by 2100) scenarios. Δ symbols denote differences between projected and actual stream temperatures obtained from the Northeast Climate Science Center. The first and second THS numbers represent statuses associated with actual and projected temperatures, respectively.

Stream name	Actual	A2	Δ	THS	B1	Δ	THS
Bark River	19.91	18.95	-0.96	BNT: 2,2	18.88	-1.03	BNT: 2,2
Bear Creek	15.75	16.54	0.79	BNT: 1,1	16.54	0.79	BNT: 1,1
Black River	15.05	14.46	-0.59	BKC: 1,1	14.36	-0.69	BKC: 1,1
Boardman River	15.02	14.88	-0.14	BKC: 1,1	14.85	-0.17	BKC: 1,1
				BNT: 1,1			BNT: 1,1
Bryan Creek	16.66	15.27	-1.39	BKC: 2,1	15.06	-1.60	BKC: 2,1
Canada Creek	19.95	19.41	-0.54	BKC: 2,2	19.09	-0.86	BKC: 2,2
Carp River	17.61	17.05	-0.56	BKC: 2,2	17.00	-0.72	BKC: 2,2
				BNT: 2,2			BNT: 2,2
				RNT: 2,2			RNT: 2,2
Cedar Creek	18.30	18.27	-0.04	BKC: 2,2	18.32	0.02	BKC: 2,2
				BNT: 2,2			BNT: 2,2
Cedar River (SLP)	17.15	16.59	-0.56	BNT: 2,1	16.46	-0.69	BNT: 2,1
Chocolay River	15.23	14.77	-0.46	RNT: 1,1	14.52	-0.71	RNT: 1,1
Davenport Creek	11.50	11.39	-0.11	RNT: 1,1	11.34	-0.16	RNT: 1,1
Duke Creek	15.32	14.69	-0.63	BKC: 1,1	14.73	-0.59	BKC: 1,1
				BNT: 1,1			BNT: 1,1
E. Branch Fox River	14.23	13.76	-0.47	BKC: 1,1	13.62	-0.61	BKC: 1,1
				BNT: 1,1			BNT: 1,1
Elm River	17.48	16.96	-0.52	RNT: 2,2	16.40	-1.10	RNT: 2,2
Escanaba River	19.95	18.88	-1.07	BKC: 2,2	18.45	-1.50	BKC: 2,2
				BNT: 2,2			BNT: 2,2
Iron River	18.61	18.53	-0.08	BKC: 2,2	18.34	-0.27	BKC: 2,2
Little Indian River	16.16	16.09	-0.07	BKC: 1,1	16.03	-0.13	BKC: 1,1
Little Muskegon River	19.89	19.24	-0.65	RNT: 2,2	19.22	-0.67	RNT: 2,2
Manistee River	13.55	13.29	-0.26	BKC: 1,1	13.29	-0.26	BKC: 1,1
				BNT: 1,1			BNT: 1,1
				RNT: 1,1			RNT: 1,1
Martin Creek	18.33	17.86	-0.47	BKC: 2,2	17.87	-0.46	BKC: 2,2
Pere Marquette River	16.62	16.41	-0.21	BNT: 2,2	16.41	-0.21	BNT: 2,2
Pigeon River	14.45	14.12	-0.33	BNT: 1,1	14.10	-0.35	BNT: 1,1
				RNT: 1,1			RNT: 1,1

Stream name	Actual	A2	Δ	THS	B1	Δ	THS
Pine River (NLP)	15.97	15.26	-0.71	BKC: 1,1	15.27	-0.70	BKC: 1,1
				BNT: 1,1			BNT: 1,1
				RNT: 1,1			RNT: 1,1
Pine River (SLP)	18.42	17.55	-0.87	BNT: 2,2	17.56	-0.86	BNT: 2,2
Prairie Creek	18.35	16.57	-1.78	BNT: 2,1	16.64	-1.71	BNT: 2,1
Rogue River	18.36	17.95	-0.41	BNT: 2,2	17.97	-0.39	BNT: 2,2
				RNT: 2,2			RNT: 2,2
Salmon Trout River	14.62	13.51	-1.11	BKC: 1,1	13.31	-1.31	BKC: 1,1
Tahquamenon River	20.02	21.16	1.14	BNT: 3,3	20.86	0.84	BNT: 3,3
W. Branch Sturgeon River	13.30	13.12	-0.18	BKC: 1,1	13.11	-0.19	BKC: 1,1
				BNT: 1,1			BNT: 1,1
				RNT: 1,1			RNT: 1,1
Yellow Dog River	18.00	17.33	-0.67	RNT: 2,2	16.96	-1.04	RNT: 2,2

TABLE 1.4 (cont'd).

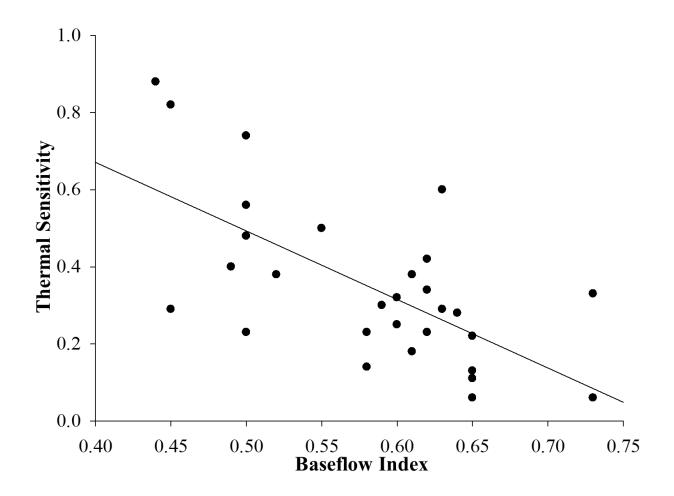


FIGURE 1.2. Relative influence of baseflow index on thermal sensitivity (i.e., air temperature regression coefficients) of streams in the State of Michigan, USA. The regression equation is: Thermal sensitivity = -1.78*Baseflow index + 1.38 (P < 0.01, $R^2 = 0.44$).

TABLE 1.5. Historical warming (1976–2006) and backcasted stream temperature change (2006-2012) for Michigan trout streams. ΔA and ΔS denote changes in air and stream temperatures over corresponding time periods. 2006 and 2012 stream temperatures were backcasted and compared to known temperatures to measure the accuracy of stream-specific temperature models. For 2006–2012, predicted changes in A and S are provided for the A2 and B1 climate forcing scenarios (B1 in parentheses). R. denotes River and Crk. denotes Creek.

Stream name	ΔA 1976-2006	ΔS 1976-2006	ΔA 2006-2012	ΔS 2006-2012
Bark R.	+ 1.72	+ 0.55	+ 1.09 (+ 1.23)	+0.35(+0.39)
Bear Crk.	+0.94	+0.22	+0.58(+0.82)	+ 0.13 (+ 0.19)
Black R.	+ 3.17	+0.92	+0.60(+0.59)	+ 0.17 (+ 0.17)
Boardman R.	+ 3.17	+0.44	- 0.56 (- 0.77)	- 0.08 (- 0.11)
Bryan Crk.	+2.33	+0.98	+ 1.01 (+ 1.48)	+ 0.43 (+ 0.62)
Canada Crk.	+ 3.17	+ 1.90	- 0.79 (- 0.59)	- 0.47 (- 0.36)
Carp R.	+ 2.00	+0.56	+ 0.65 (+ 1.14)	+ 0.18 (+ 0.32)
Cedar Crk.	+0.72	+0.40	+0.58(+0.65)	+0.33(+0.37)
Cedar R. (SLP)	+ 2.61	+0.65	- 0.68 (- 0.23)	- 0.17 (- 0.06)
Chocolay R.	+ 2.72	+0.63	- 0.64 (+ 0.43)	- 0.15 (+ 0.10)
Davenport Crk.	+ 2.00	+0.26	+0.55(+0.79)	+0.07(+0.10)
Duke Crk.	+0.72	+0.35	+0.65(+0.74)	+ 0.31 (+ 0.36)
E. Branch Fox R.	+ 2.00	+0.66	+0.56(+0.87)	+ 0.19 (+ 0.29)
Elm R.	+ 2.72	+ 2.23	+ 0.99 (+ 1.79)	+ 0.82 (+ 1.47)
Escanaba R.	+ 2.72	+ 2.40	+1.01(+1.48)	+ 0.89 (+ 1.30)
Iron R.	+ 1.89	+0.57	- 0.77 (- 0.03)	- 0.23 (- 0.01)
Little Indian R.	+ 2.72	+0.16	- 0.61 (+ 0.21)	- 0.04 (+ 0.01)
Little Muskegon R.	+2.56	+0.87	- 0.79 (- 0.80)	- 0.27 (- 0.27)
Manistee R.	+ 3.17	+ 0.41	+0.76(+0.49)	+ 0.10 (+ 0.06)
Martin Crk.	+2.11	+ 0.80	- 0.82 (- 0.83)	- 0.31 (- 0.31)
Pere Marquette R.	+2.11	+0.38	- 0.82 (- 0.83)	- 0.15 (- 0.15)
Pigeon R.	+ 3.17	+0.35	+0.67(+0.50)	+ 0.07 (+ 0.06)
Pine R. (NLP)	+ 2.11	+ 0.46	+ 0.76 (+ 0.49)	+ 0.17 (+ 0.11)

TABLE 1.5 (cont'd).

Stream name	ΔA 1976-2006	ΔS 1976-2006	ΔA 2006-2012	ΔS 2006-2012
Pine R. (SLP)	+2.56	+ 1.02	+0.68(+0.72)	+0.27(+0.29)
Prairie Crk.	+ 1.94	+ 1.44	+0.58(+0.65)	+0.43(+0.48)
Rogue R.	+0.72	+0.17	+0.65(+0.74)	+0.15(+0.17)
Salmon Trout R.	+2.33	+0.68	+ 0.99 (+ 1.79)	+ 0.29 (+ 0.52)
Tahquamenon R.	+ 2.00	+ 1.00	+ 0.75 (+ 1.32)	+0.38(+0.66)
W. Branch Sturgeon R.	+3.17	+ 0.19	+0.67 (+0.50)	+0.04(+0.03)
Yellow Dog R.	+2.33	+0.89	- 0.63 (+ 0.39)	- 0.24 (+ 0.15)

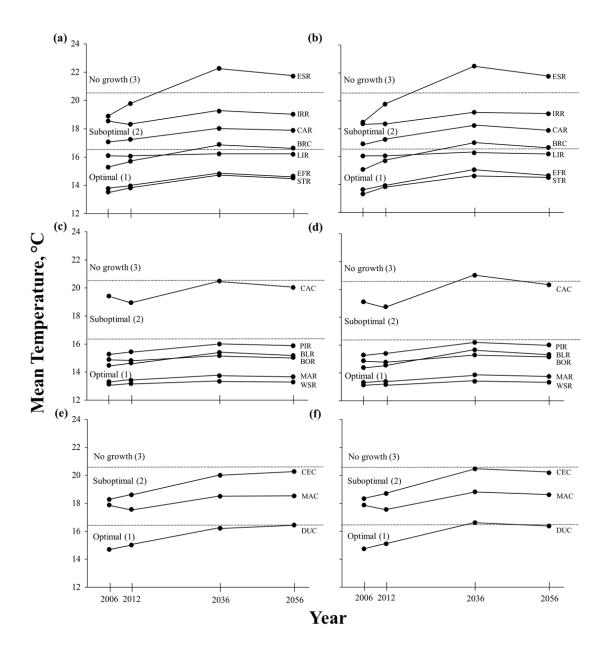


FIGURE 1.3. Projected temperatures in individual Michigan brook charr streams in 2006, 2012, 2036, and 2056 under A2 (820 ppm atmospheric CO₂ by 2100) and B1 (550 ppm by 2100) scenarios. Plots are organized by region and emissions scenario: (a) Upper Peninsula, A2 scenario; (b) Upper Peninsula, B1 scenario; (c) northern Lower Peninsula, A2 scenario; (d) northern Lower Peninsula, B1 scenario; (e) southern Lower Peninsula, A2 scenario; (f) southern Lower Peninsula, B1 scenario. Dotted lines represent transitions between thermal habitat suitability statuses. Stream abbreviations are as follows: BRC = Bryan Creek, BLR = Black River, BOR = Boardman River, CAC = Canada Creek, CAR = Carp River, CEC = Cedar Creek, DUC = Duke Creek, EFR = East Branch Fox River, ESR = Escanaba River, IRR = Iron River, LIR = Little Indian River, MAR = Manistee River, MAC = Martin Creek, PIR = Pine River (northern Lower Peninsula), STR = Salmon Trout River, WSR = West Branch Sturgeon River.

become unsuitable for growth in the Escanaba River with projected warming by 2.49°C (A2 scenario) and 2.73°C (B1 scenario; Table 1.6). Habitat suitability was predicted to remain the same from 2036 to 2056 under both scenarios in all brook charr streams evaluated.

In the NLP from 2006 to 2056, thermal habitat was projected to be optimal in most streams (Black, Boardman, Manistee, Pine, West Branch Sturgeon rivers) under the A2 and B1 scenarios (Figure 1.3c,d). From 2012 to 2036, thermal habitat was forecasted to become unsuitable for growth in Canada Creek under the B1 scenario with predicted warming by 2.27°C (Figure 1.3d; Table 1.6). In the SLP under the A2 and B1 scenarios, thermal habitat was predicted to be suboptimal from 2006 to 2056 in Martin Creek and Cedar Creek (Figure 1.3e,f). From 2012 to 2036 under the B1 scenario, thermal habitat was forecasted to become suboptimal in Duke Creek with predicted warming by 1.51°C (Figure 1.3f; Table 1.6).

Thermal habitat suitability: Brown trout

From 1976 to 2006, the mean temperature of brown trout streams increased by 0.65°C as mean air temperature increased by 2.09°C (Table 1.5). In the UP under the A2 and B1 scenarios, thermal habitat suitability was predicted to be optimal in the East Branch Fox River from 2006 to 2056 (Figure 1.4a,b). From 2006 to 2012, thermal habitat suitability was projected to be optimal in the Bark River, suboptimal in the Escanaba River, and unsuitable in the Tahquamenon River under both scenarios (Figure 1.4a,b). During the same time period, thermal habitat was forecasted to be suboptimal in the Carp River under the B1 scenario with predicted warming by 0.32°C (Table 1.5). From 2012 to 2036, thermal habitat was projected to be unsuitable for growth in the Escanaba River with predicted warming by 2.49°C (A2 scenario) and 2.73°C (B1 scenario; Table 1.6). From 2036 to 2056, habitat suitability was predicted to remain the same

TABLE 1.6. Projected future warming (2012–2036, 2036–2056) for Michigan trout streams. ΔA and ΔS denote changes in air and stream temperatures over corresponding time periods. Predicted changes in A and S are provided for the A2 and B1 climate forcing scenarios (B1 in parentheses). R. denotes River and Crk. denotes Creek.

Stream name	ΔA 2012-2036	ΔS 2012-2036	ΔA 2036-2056	ΔS 2036-2056
Bark R.	+ 2.74 (+ 3.16)	+ 0.88 (+ 1.01)	- 0.69 (- 0.65)	- 0.22 (- 0.21)
Bear Crk.	+ 2.40 (+ 3.10)	+ 0.55 (+ 0.71)	+ 0.72 (- 0.29)	+ 0.17 (- 0.07)
Black R.	+ 2.58 (+ 3.79)	+ 0.75 (+ 1.10)	- 0.77 (- 1.15)	- 0.22 (- 0.33)
Boardman R.	+ 2.49 (+ 3.77)	+0.35(+0.53)	- 0.87 (- 1.04)	- 0.12 (- 0.15)
Bryan Crk.	+ 2.83 (+ 3.11)	+ 1.19 (+ 1.31)	- 0.62 (- 0.83)	- 0.26 (- 0.35)
Canada Crk.	+ 2.58 (+ 3.79)	+ 1.55 (+ 2.27)	- 0.77 (- 1.15)	- 0.46 (- 0.69)
Carp R.	+ 2.78 (+ 3.62)	+ 0.78 (+ 1.01)	- 0.49 (- 1.29)	- 0.14 (- 0.36)
Cedar Crk.	+ 2.48 (+ 3.14)	+ 1.39 (+ 1.76)	+ 0.48 (- 0.49)	+ 0.27 (- 0.28)
Cedar R. (SLP)	+ 2.74 (+ 3.16)	+0.69(+0.79)	- 0.69 (- 0.65)	- 0.17 (- 0.16)
Chocolay R.	+ 2.71 (+ 3.36)	+0.62(+0.77)	- 0.42 (- 1.31)	- 0.10 (- 0.30)
Davenport Crk.	+ 2.63 (+ 3.53)	+0.34(+0.46)	- 0.54 (- 1.26)	- 0.07 (- 0.16)
Duke Crk.	+ 2.48 (+ 3.14)	+ 1.19 (+ 1.51)	+ 0.48 (- 0.49)	+ 0.23 (- 0.24)
E. Branch Fox R.	+ 2.61 (+ 3.44)	+ 0.86 (+ 1.14)	- 0.50 (- 1.27)	- 0.17 (- 0.42)
Elm R.	+ 3.19 (+ 2.65)	+ 2.62 (+ 2.17)	- 0.75 (- 0.39)	- 0.62 (- 0.32)
Escanaba R.	+ 2.83 (+ 3.11)	+ 2.49 (+ 2.73)	- 0.62 (- 0.83)	- 0.54 (- 0.73)
Iron R.	+ 3.13 (+ 2.82)	+0.94(+0.85)	- 0.74 (- 0.35)	- 0.22 (- 0.11)
Little Indian R.	+ 2.61 (+ 3.44)	+ 0.16 (+ 0.21)	- 0.50 (- 1.27)	- 0.03 (- 0.08)
Little Muskegon R.	+ 2.48 (+ 3.41)	+0.84(+1.16)	- 0.12 (- 0.72)	- 0.04 (- 0.24)
Manistee R.	+ 2.47 (+ 3.56)	+0.32(+0.46)	- 0.54 (- 0.81)	- 0.07 (- 0.11)
Martin Crk.	+ 2.48 (+ 3.32)	+ 0.94 (+ 1.26)	+ 0.05 (- 0.55)	+ 0.02 (- 0.21)
Pere Marquette R.	+ 2.48 (+ 3.32)	+0.45(+0.60)	+ 0.05 (- 0.55)	+ 0.01 (- 0.10)
Pigeon R.	+ 2.52 (+ 3.78)	+0.28(+0.42)	- 0.83 (- 1.11)	- 0.09 (- 0.12)
Pine R. (NLP)	+ 2.47 (+ 3.56)	+0.54(+0.78)	- 0.54 (- 0.81)	- 0.12 (- 0.18)

TABLE 1.6 (cont'd).

Stream name	ΔA 2012-2036	ΔS 2012-2036	ΔA 2036-2056	ΔS 2036-2056
Pine R. (SLP)	+ 2.49 (+ 3.25)	+ 1.00 (+ 1.30)	+ 0.23 (- 0.69)	+ 0.09 (- 0.27)
Prairie Crk.	+ 2.48 (+ 3.14)	+ 1.83 (+ 2.32)	+ 0.48 (- 0.49)	+ 0.35 (- 0.37)
Rogue R.	+ 2.48 (+ 3.14)	+ 0.57 (+ 0.72)	+ 0.48 (- 0.49)	+ 0.11 (- 0.11)
Salmon Trout R.	+ 3.19 (+ 2.65)	+0.92(+0.77)	- 0.75 (- 0.39)	- 0.22 (- 0.11)
Tahquamenon R.	+ 2.72 (+ 3.51)	+ 1.36 (+ 1.75)	- 0.41 (- 1.36)	- 0.21 (- 0.68)
W. Branch Sturgeon R.	+ 2.52 (+ 3.78)	+ 0.15 (+ 0.23)	- 0.83 (- 1.11)	- 0.05 (- 0.07)
Yellow Dog R.	+ 2.98 (+ 2.96)	+ 1.13 (+ 1.13)	- 0.63 (- 0.81)	- 0.24 (- 0.31)

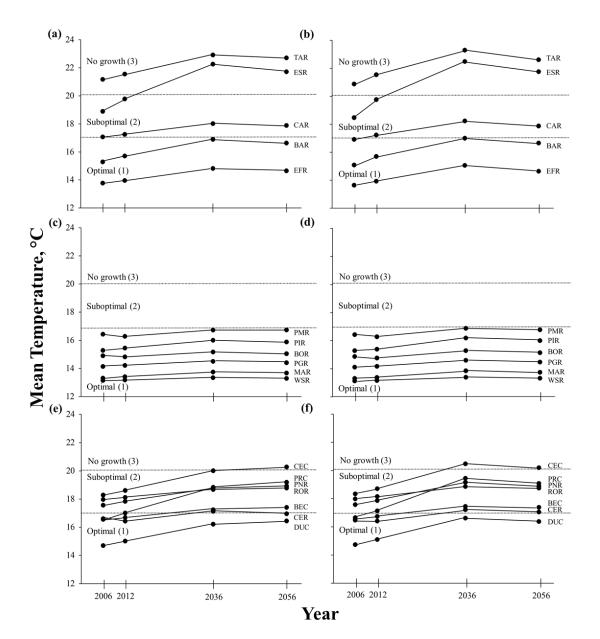


FIGURE 1.4. Projected temperatures in individual Michigan brown trout streams in 2006, 2012, 2036, and 2056 under A2 (820 ppm atmospheric CO₂ by 2100) and B1 (550 ppm by 2100) scenarios. Plots are organized by region and emissions scenario: (a) Upper Peninsula, A2 scenario; (b) Upper Peninsula, B1 scenario; (c) northern Lower Peninsula, A2 scenario; (d) northern Lower Peninsula, B1 scenario. (e) southern Lower Peninsula, A2 scenario; (f) southern Lower Peninsula, B1 scenario. Dotted lines represent transitions between thermal habitat suitability statuses. Stream abbreviations are as follows: BEC = Bear Creek, BOR = Boardman River, BRC = Bryan Creek, CAR = Carp River, CEC = Cedar Creek, CER = Cedar River, DUC = Duke Creek, EFR = East Branch Fox River, ESR = Escanaba River, MAR = Manistee River, PMR = Pere Marquette River, PGR = Pigeon River, PNR = Pine River (southern Lower Peninsula), PIR = Pine River (northern Lower Peninsula), PRC = Prairie Creek, ROR = Rogue River, TAR = Tahquamenon River, WSR = West Branch Sturgeon River.

under both scenarios in all brown trout streams evaluated.

In the NLP from 2006 to 2056, thermal habitat was forecasted to be optimal under the A2 and B1 scenarios in all brown trout streams evaluated, including the Boardman, Manistee, Pere Marquette, Pigeon, Pine, and West Branch Sturgeon rivers (Figure 1.4c,d). In the SLP under the A2 and B1 scenarios, thermal habitat suitability was predicted to be optimal in Duke Creek and suboptimal in the Rogue River from 2006 to 2056 (Figure 1.4e,f). From 2006 to 2012, thermal habitat was projected to be optimal in the Cedar River and suboptimal in Cedar Creek and the Pine River under both scenarios. During the same time period, thermal habitat was predicted to be suboptimal in Prairie Creek under the B1 scenario with projected warming by 0.48°C (Table 1.5). From 2012 to 2036, thermal habitat was forecasted to be suboptimal in the Cedar River and Bear Creek and unsuitable for growth in Cedar Creek under both scenarios. From 2036 to 2056 under the A2 scenario, thermal habitat was projected to be optimal in the Cedar Creek under both scenarios. From 2036 to 2056 under the A2 scenario, thermal habitat was projected to be optimal in the Cedar River and unsuitable for growth in Cedar Creek with predicted cooling and warming by 0.17°C and 0.27°C, respectively (Figure 1.4e; Table 1.6). Thermal habitat suitability was forecasted to remain the same from 2036 to 2056 under the B1 scenario in all brown trout streams evaluated (Figure 1.4f).

Thermal habitat suitability: Rainbow trout

From 1976 to 2006, the mean water temperature of brown trout streams increased by 0.64°C (air temperature +2.42°C; Table 1.5). In the UP under the A2 and B1 scenarios, thermal habitat suitability was predicted to be optimal in the Chocolay River and Davenport Creek and suboptimal in the Carp, Elm, and Yellow Dog Rivers from 2006 to 2056 (Figure 1.5a,b). Similarly, thermal habitat was projected to be optimal (Manistee, Pigeon, Pine, and West Branch Sturgeon rivers) and suboptimal (Little Muskegon River) in the NLP from 2006 to 2056 under

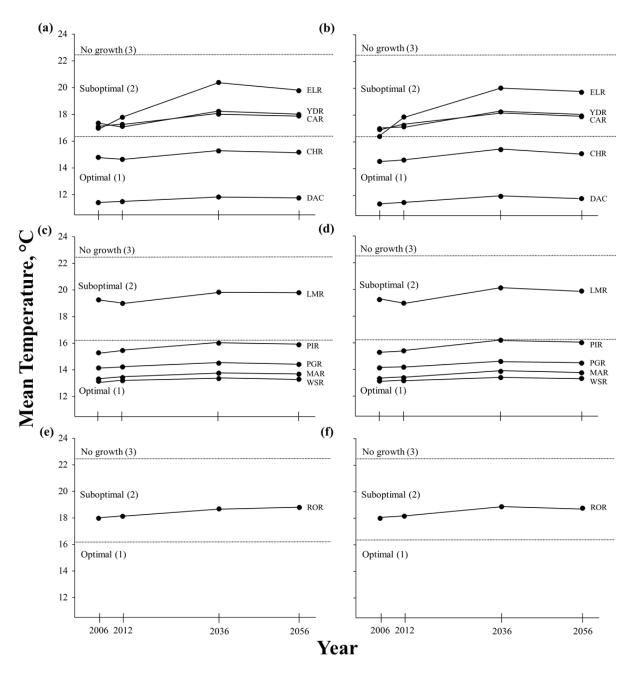


FIGURE 1.5. Projected temperatures in individual Michigan rainbow trout streams in 2006, 2012, 2036, and 2056 under A2 (820 ppm atmospheric CO_2 by 2100) and B1 (550 ppm by 2100) scenarios. Plots are organized by region and emissions scenario: (a) Upper Peninsula, A2 scenario; (b) Upper Peninsula, B1 scenario; (c) northern Lower Peninsula, A2 scenario; (d) northern Lower Peninsula, B1 scenario. Dotted lines represent transitions between thermal habitat suitability statuses. Stream abbreviations are as follows: CAR = Carp River, CHR = Chocolay River, DAC = Davenport Creek, ELR = Elm River, LMR = Little Muskegon River, MAR = Manistee River, PGR = Pigeon River, PIR = Pine River, ROR = Rogue River, WSR = West Branch Sturgeon River, YDR = Yellow Dog River.

the A2 and B1 scenarios (Figure 1.5c,d). Thermal habitat in the Rogue River, the only rainbow trout stream in the SLP, was predicted to be suboptimal under both emissions scenarios from 2006 to 2056 (Figure 1.5e,f).

Discussion

Our study is the first broad-scale investigation of climate-driven stream temperature warming in Michigan with implications for salmonid management. Water temperatures were projected to increase by 0.19–5.94°C in 30 coldwater salmonid streams over the next 40 years due to predicted air temperature warming. This finding supports a previous study in the State Minnesota, USA (Pilgrim et al. 1998), in which temperatures in 39 streams increased by 0.30– 6.90° C under a doubling of atmospheric CO₂ concentrations comparable to the A2 climate forcing scenario. In addition, our study supports a previous investigation in the State of Wisconsin, USA (Lyons et al. 2010), in which thermal habitat degradation was projected for brook charr and brown trout in 282 streams forecasted to warm by 0.80–4.00°C over the next 45 years. In our research, the magnitude of warming and thermal habitat impairment varied among streams and time periods, with the greatest warming and habitat degradation occurring from 1976–2006 (2.72°C) and projected from 2012–2036 (2.49–2.62°C) in the Elm and Escanaba rivers, systems with the lowest BFI (< 0.45). In contrast, the magnitude of warming from 1976– 2006 (0.16–0.66 °C) and projected warming from 2012–2036 (0.16–0.86°C) was considerably lower the East Branch Fox and Little Indian rivers, systems with the highest BFI (0.73). This finding supported our hypothesis that temperature and thermal habitat alterations would vary spatially and temporally due to system-specific patterns of warming. It also reinforces previous research indicating fish assemblages in Michigan streams with stable discharge from

groundwater inputs are more resilient to thermal warming than those in streams with less stable discharge (Zorn et al. 2012). Thermal habitat degradation was projected to occur least frequently in rainbow trout streams as this species has a wider temperature range (12.0–22.5°C) for growth and survival compared to brook charr (11.0–20.5°C) and brown trout (12.0–20.0°C) (Wurtsbaugh and Davis 1977).

Warmer air temperatures are projected to increase stream temperatures both directly (i.e., advection) and indirectly through effects on precipitation, evaporation, and transpiration. Predicted effects of climate change include more variable (and overall lower) precipitation (Parry et al. 2007; Stoner et al. 2012), increased evaporation (Compagnucci et al. 2001), and decreased discharge. These impacts would increase stream temperature by reducing the volume of water exposed to solar radiation. However, in Michigan streams near the Great Lakes, precipitation will likely intensify in fall and winter due to predicted increases in snowfall (Norton and Bolsenga 1993; Primack 2000), increasing surface runoff and water volume and decreasing temperature compared to systems without this source of precipitation (Kurylyk et al. 2013). Increased canopy and soil surface evaporation is projected to decrease groundwater recharge and increase water temperature (Ge et al. 2013), although streams high BFI are expected to warm at a slower rate than those with low BFI due to groundwater-driven thermal buffering (Menberg et al. 2014). Transpiration of water from plants has been reported to contribute to stream warming by reducing streamflow and groundwater recharge (Federer and Lash 1978; Bond et al. 2002). Effects of climate warming on transpiration and stream temperature will depend largely on changes in the species composition and leaf characteristics (e.g., stomatal conductance, water use-efficiency) of riparian plants and trees (Compagnucci et al. 2001; Kirschbaum 2004). We encourage researchers to incorporate the thermal effects of transpiration, riparian shading, and

watershed land cover (Wehrly et al. 1997; Wiley et al. 2010) into future stream temperature modeling to improve predictive accuracy.

Projected increases in Michigan stream temperatures will result in thermal habitat conditions less conducive for salmonid growth and survival during the warmest period of the year (Raleigh 1982a,b; Raleigh et al. 1986), particularly in thermally sensitive streams with low BFI values. This will likely be manifested by declines in availability and changes in spatial arrangement of optimal thermal habitat, with potential effects on salmonid distribution and survival. For instance, if stream warming restricts coldwater habitats to specific areas (e.g., headwater reaches), salmonid populations will become isolated, which could increase interspecific competition and decrease survival (Tsuboi et al. 2013; Dugdale et al. 2015). Previous research in Michigan's Muskegon River suggested warmer water temperatures resulting from climate change will restrict the distribution and decrease the survival of brook charr, brown trout, and rainbow trout (Steen et al. 2010). Researchers in the State of Wisconsin, USA, predicted that by 2060 the total length of streams suitable for brown trout would decline by 8, 33, and 88 percent under limited (summer air temperatures increase 1.0° C and water 0.8° C), moderate (air 3.0° C and water 2.4° C), and major (air 5.0° C and water 4.0° C) climatic warming (Lyons et al. 2010). Results were more extreme for brook charr, with distributional declines of 44 and 94 percent under limited and moderate warming, and complete extirpation under major warming. Although our models did not project extirpation of any species in the Michigan streams evaluated, summer growth limitation may be coupled with decreased reproduction as lower oxygen levels resulting from stream temperature warming and/or groundwater withdrawal may reduce egg survival or prevent spawning (Raleigh 1982a,b; Raleigh et al, 1986). Although annual salmonid growth may remain stable or increase due to longer growing season length and

increased prey availability, projected reductions in growth and survival during the warmest period of the year have important management implications.

Management implications

We encourage scientists, biologists, policy makers, and public stakeholders to collaboratively develop resilience-based management programs to conserve salmonid populations amidst global change. Our research represents a step in this direction as it projects consequences of stream thermal warming for salmonid growth and survival in Michigan. Our results indicate it is important for fisheries professionals to manage streams for thermal resilience by forming public-private partnerships to protect watershed land cover types that facilitate high groundwater recharge (e.g., grasslands; Waco and Taylor 2010; Siitari et al. 2011), preserve riparian vegetation and associated shading (Blann et al. 2002), and maintain longitudinal connectivity to promote salmonid movement to cold headwater reaches (Drake and Taylor 1996; Hayes et al. 1998). We recommend these strategies play prominent roles in resilience-based management programs for coldwater streams and their important salmonid fisheries. As documented in our study, streams with low thermal sensitivity (i.e., high BFI) will likely maintain thermal conditions (e.g., cool summer temperatures, seasonal flow stability; Wiley et al. 1997; Baker et al. 2003) that are more conducive for salmonid growth and survival than systems with high thermal sensitivity in the next 40 years. Thus, we encourage managers to allocate resources (i.e., time, money, personnel) to prioritize protection of streams with low thermal sensitivity and inform public stakeholders about realistic expectations for stream fish communities amidst global change (e.g., salmonid decline, centrarchid expansion; Pease and Paukert 2014). Moreover, because streams with high BFI were less susceptible to temperature

change, we suggest managers use spatial BFI maps as tools for understanding stream thermal sensitivity across large geographic areas. Moreover, we encourage managers to increase the spatial and temporal coverage of air and stream temperature monitoring networks and thereby expand their utility for salmonid management.

Fisheries professionals and public stakeholders can also collaboratively implement additional strategies for resilience-based salmonid management. They can promote thermally resilient salmonid populations by removing dams and installing fish ladders at roadside crossings and culverts to restore stream habitat connectivity, particularly in cold headwater reaches, which function as thermal refugia during warm summer months. Fisheries professionals can also foster salmonid population resilience by implementing regulations (e.g., protected slot limits, reduced creel limits) that reduce harvest and increase survival during thermally stressful periods. In addition, we recommend fisheries professionals protect a diversity of salmonid size classes, genetic stocks, and prey species that tolerate a wide range of temperatures predicted from climate change models (Hansen et al. 2015). We encourage fisheries managers and policy makers to provide incentives (e.g., financial assistance, open space tax deduction, fast-track permitting; Knight 2009) for land developers and property owners to protect coldwater habitat and thermal buffering mechanisms on their lands. Moreover, because it is infeasible to protect salmonid populations and thermal habitat in all streams, it will be necessary for fisheries professionals to implement a triage approach with specific criteria for stream protection (e.g., species composition, habitat quality, recreational importance). In summary, resilience-based salmonid management programs will require effective collaboration among scientists, biologists, policy makers, and public stakeholders. Our research promotes resilience-based salmonid management by providing a methodology to project stream temperature and thermal habitat suitability.

Fisheries professionals can use this approach to protect coldwater habitats and drivers of stream cooling and ultimately conserve resilient salmonid populations amidst global change.

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CHAPTER 2: COMPARING STREAM-SPECIFIC TO GENERALIZED TEMPERATURE MODELS TO GUIDE COLDWATER SALMONID MANAGEMENT IN A CHANGING CLIMATE

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Abstract

Global climate change is predicted to increase air and stream temperatures and alter thermal habitat suitability for growth and survival of coldwater fishes, including brook charr (Salvelinus fontinalis), brown trout (Salmo trutta), and rainbow trout (Oncorhynchus mykiss). In a changing climate, accurate stream temperature modeling is increasingly important for sustainable salmonid management throughout the world. However, finite resource availability (e.g. funding, personnel) drives a tradeoff between thermal model accuracy and efficiency (i.e. cost-effective applicability at management-relevant spatial extents). Using different projected climate change scenarios, we compared the accuracy and efficiency of stream-specific and generalized (i.e. region-specific) temperature models for coldwater salmonids within and outside the State of Michigan, USA, a region with long-term stream temperature data and productive coldwater fisheries. Projected stream temperature warming between 2016 and 2056 ranged from 0.1 to 3.8° C in groundwater-dominated streams and 0.2 to 6.8° C in surface-runoff dominated systems in the State of Michigan. Despite their generally lower accuracy in predicting exact stream temperatures, generalized models accurately projected salmonid thermal habitat suitability in 82 % of groundwater-dominated streams, including those with brook charr (80 % accuracy), brown trout (89 % accuracy), and rainbow trout (75 % accuracy). In contrast, generalized models predicted thermal habitat suitability in runoff-dominated streams with much lower accuracy (54 %). These results suggest that, amidst climate change and constraints in resource availability, generalized models are appropriate to forecast thermal conditions in groundwater-dominated streams within and outside Michigan and inform regional-level salmonid management strategies that are practical for coldwater fisheries managers, policy makers, and the public. We recommend fisheries professionals reserve resource-intensive

stream-specific models for runoff-dominated systems containing high-priority fisheries resources (e.g. trophy individuals, endangered species) that will be directly impacted by projected stream warming.

KEYWORDS: brook charr, brown trout, climate change, coldwater fisheries, rainbow trout, temperature

Introduction

Streams and rivers cover 0.30–0.56% of globe across a fluvial area of 485,000–682,000 km² (Downing et al. 2012). Climate change is projected to increase stream and river temperatures and alter their thermal habitat suitability for growth, reproduction, and survival of resident fishes (Pilgrim et al. 1998; Lyons et al. 2010; Carlson et al. 2017). In addition, warmer air temperatures are predicted to increase stream and river temperatures indirectly through more variable (and overall lower) precipitation (Stoner et al. 2013), increased evaporation (Compagnucci et al. 2001), and thus decreased groundwater discharge into these river systems. Salmonids such as brook charr (Salvelinus fontinalis), brown trout (Salmo trutta), and rainbow trout (Oncorhynchus mykiss) are coldwater fishes with laboratory temperature preferenda less than or equal to 20° C and critical thermal maxima less than or equal to 31° C (Raleigh 1982a, b; Raleigh et al. 1986; Lyons et al. 2009). These species support ecologically, socioeconomically, and culturally important fisheries in North America, South America, Europe, and parts of Asia and Australia (MacCrimmon 1972; Budy et al. 2013; Weber et al. 2015). As such, understanding the effects of climate change on these valuable species will have economic and social ramifications for the management of coldwater stream fisheries throughout the world.

Temperature regulates fish metabolism, growth, reproduction, and survival (Dodds and Whiles 2010; Isaak et al. 2012), all of which affect fish recruitment and fisheries productivity. Temperatures above species-specific thermal maxima cause mortality, whereas temperatures at or below maxima alter individual growth and reproduction (Magnuson et al. 1997). Predicted climate-driven increases in stream temperatures are likely to decrease the thermal habitat suitability of coldwater streams for growth and survival of brook charr, brown trout, and rainbow trout because these species have relatively low thermal tolerances to warm temperatures (Fry et

al. 1946; Raleigh 1982a, b; Raleigh et al. 1986). Despite the importance of climate-changeinduced temperature increases of riverine ecosystems throughout the world (Kaushal et al. 2010; van Vliet et al. 2013), there is widespread scarcity in the availability of long-term stream temperature datasets throughout the world. This data deficiency impedes or prevents development of region- and stream-specific temperature models and inhibits the prediction and mitigation of the ecological and social effects of stream warming on salmonid fisheries (e.g. fragmented species distribution, reduced socioeconomic output). Collectively, the global distribution and importance and stream salmonids, the global scope of climate change, and the general dearth of long-term stream temperature data indicate the importance of developing accurate, efficient approaches for projecting effects of climate change on coldwater streams and designing data-limited strategies for sustainable salmonid management in a warming world.

Fisheries management is broadly defined as the process of using information (e.g. ecological, economic, social, political) to develop strategies for achieving goals established for fisheries resources (Kruger and Decker 1999). Decision-making is fundamental to fisheries management and necessitates informed choices regarding allocation of finite resources (e.g. funding, time, personnel) to achieve the goals set for specific fisheries systems. For example, to mitigate the effects of climate change on coldwater stream ecosystems, fisheries professionals must understand how stream temperature is regulated by ambient atmospheric conditions (e.g. air temperature) and also influenced by meteorological (e.g. solar radiation, wind, humidity) and hydrological (e.g. discharge, depth, groundwater input) conditions in stream watersheds (Gu et al. 1998; Pilgrim et al. 1998). With this knowledge, fisheries professionals can make informed temperature modeling decisions, including which models and variables to use, amidst constraints

in resource availability and, ultimately, which thermal habitat management strategies to implement for mitigation purposes.

Heat budget models generally predict water temperatures with high accuracy (i.e. exactness of temperature projection) because they prioritize the relative influence of the various atmospheric, meteorological, and hydrological drivers of stream temperature (O'Driscoll and DeWalle 2006; Wehrly et al. 2009). However, these models generally require extensive and expensive data collection protocols for small spatial extents (e.g. stream reaches), limiting their applicability at the regional scales (e.g. watersheds) where fisheries management agencies typically operate (Anonymous 2000; WDNR 2002; MNDNR 2011). As a result, alternative approaches such as air-stream temperature regression models are often less complex, more cost-effective (i.e. same accuracy at lower cost), and more spatially appropriate than heat budget models (Mohseni et al. 1998; Benyahya et al. 2007), making them more useful for fisheries management agencies when managing for most fish species of interest.

In lieu of heat budget models, fisheries professionals currently use two broad approaches to describe the relationship between air temperature and stream temperature: stream-specific models and generalized models. Stream-specific temperature models account for the unique combination of factors that influence each stream's thermal regime (e.g. air temperature, discharge, groundwater input), whereas generalized models are region-specific in representing the thermal regimes of all streams in a particular area. Stream-specific models treat each stream as a distinct system with a thermal regime influenced by discrete factors, whereas generalized models assume that regional patterns in air temperature, as opposed to system-specific characteristics, are the primary drivers of water temperature (Stefan and Preud'homme 1993; Krider et al. 2013). Each modeling approach has advantages and disadvantages. Generalized

models may be less accurate than stream-specific models in predicting exact water temperatures, but their development requires significantly lower investments of funding, time, and personnel as streams do not have to be monitored individually. In contrast, stream-specific models are generally more accurate than generalized models but require significantly more resources to develop. In addition, fisheries management strategies (e.g. harvest regulations) implemented based on stream-specific models may be cumbersome to implement because they will likely be unique to – and thus variable among – individual streams reaches.

Many U.S. states (e.g. Michigan, Wisconsin, Minnesota; Anonymous 2000; WDNR 2002; MNDNR 2011) already manage streams on a regional basis, aligning more closely with the generalized, rather than stream-specific, temperature modeling framework. However, the tradeoffs associated with stream-specific and generalized models are important to consider in evaluating the accuracy and efficiency (i.e. cost-effective applicability at management-relevant spatial extents) of each modeling approach to achieve specific management objectives for sustaining stream salmonid fisheries in a changing climate.

Comparing stream-specific and generalized temperature models necessitates the availability of long-term (i.e. ≥ 10 year) stream temperature data. Although long time-series stream temperature data sets are relatively uncommon, fisheries professionals in the State of Michigan, USA, have monitored temperatures in many trout streams for 10–20 years, making it an ideal study area in which to compare stream-specific and generalized models. Brook charr, brown trout, and rainbow trout are ecologically and socio-economically important fishes in Michigan (Godby et al. 2007), serving as keystone predators in coldwater streams and supporting valuable recreational fisheries in which more than 585,000 anglers spent 8.2 million angling days in 2011 (USFWS 2011). In Michigan, projected air temperature warming is predicted to increase

summer temperatures in coldwater streams by 0.19–5.49° C from 2016 to 2056 (Carlson et al. 2017) and decrease thermal habitat availability and salmonid growth in systems that exceed thermal optima during the warmest period of the year (i.e. July; Zorn et al. 2011). Although Carlson et al. (2017) used stream-specific models to project future water temperatures in Michigan streams, the present study expands upon previous work by explicitly comparing stream-specific and generalized models to inform stream salmonid management amidst climate change and limitations in the availability of funding, time, and personnel.

The goal of this study was to evaluate the impact of warming water temperatures on salmonid growth and survival in coldwater streams in select areas of North America. Two modeling approaches were used to predict thermal habitat changes: stream-specific and generalized models. These models were chosen as they are spatially and temporally robust and thus can inform salmonid management approaches amidst a changing climate and resource limitations. As such, this study was intended to lay a conceptual foundation for future studies in other areas of the world with coldwater streams and fish populations susceptible to climate change. The specific objectives of this study were to: (1) measure the accuracy of stream-specific and generalized models in predicting water temperature and thermal habitat suitability for salmonid growth and survival in streams in the State of Michigan and the eastern USA that span latitudinal and hydrological gradients and support socioeconomically valuable salmonid populations; (2) forecast future water temperatures and thermal habitat suitability in these streams a in select future years (i.e. 2036, 2056); and, (3) evaluate the accuracy and efficiency of stream-specific and generalized models to develop a model comparison approach that can be used for salmonid management programs within and outside Michigan.

Methods

Study area

Fifty-two coldwater salmonid streams were selected throughout Michigan based on latitudinal, hydrological, and recreational criteria (Figure 2.1, Table 2.1). Streams spanned a latitudinal thermal gradient from north to south. Base flow, the component of streamflow attributable to groundwater, varied among streams such that they covered a gradient from surface-runoff to groundwater dominance (see "Baseflow measurements" below) over which brook charr, brown trout, and rainbow trout occur in Michigan. In addition, all streams were important from a fisheries management perspective as they support productive recreational fisheries for brook charr, brown trout, or rainbow trout. These species are widely distributed throughout Michigan (Zorn et al. 2011, 2012), making them effective indicator species for evaluating the impact of climate change on coldwater stream fishes adapted to groundwaterdominated and surface runoff-dominated streams. Overall, brook charr were found in 28 of the streams evaluated, brown trout in 26 streams, and rainbow trout in 21 streams. Seventeen of the streams studied supported more than one salmonid species, and six streams supported all three species (Table 2.1).

Baseflow measurements

A United States Geological Survey report of base flow (Neff et al. 2005) was used to obtain each study stream's base flow index (BFI), a value that represents the mean rate of base flow (mm*yr⁻¹) divided by the corresponding mean rate of total streamflow (mm*yr⁻¹) and ranges from zero (i.e. no groundwater) to one (i.e. all groundwater; Wahl and Wahl 1988). All BFI calculations were made using a digital filter hydrograph separation technique (Arnold and

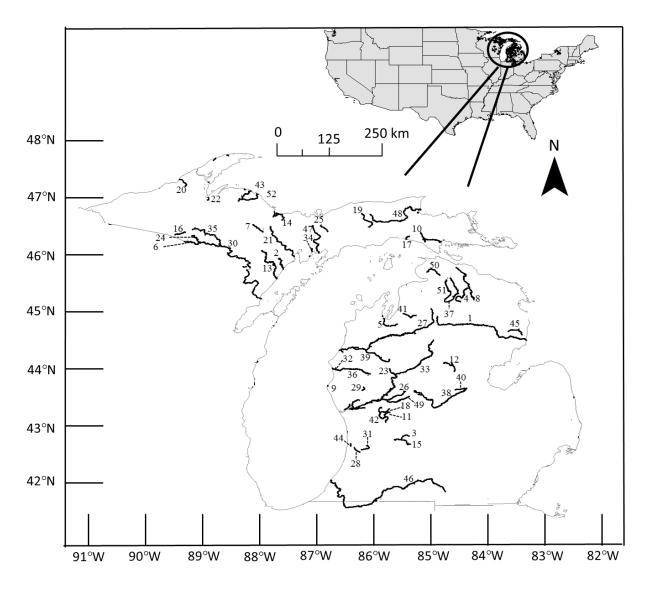


FIGURE 2.1. Map of 52 brook charr, brown trout, and rainbow trout streams used for air-stream temperature modeling in Michigan. Streams and corresponding identification numbers are listed in Table 1. Modified from Carlson et al. (2017).

TABLE 2.1. Descriptive information about 52 streams used for temperature modeling in Michigan, USA. Sub-basin denotes the National Hydrography Dataset sub-basin (i.e. 8-digit Hydrologic Unit Code). Map number refers to stream identifiers in Figure 2.1. Type denotes hydrological influence: groundwater-dominated (GD) streams were distinguished from surfacerunoff dominated (RD) systems using a threshold base-flow index (i.e. > 0.60; Neff et al. 2005). Species: brook charr [BKC], brown trout [BNT], rainbow trout [RBT]). Area: drainage area, km². Elevation: mean catchment elevation, m. Asterisks indicate that streams had historical fieldcollected air and stream temperatures for development of stream-specific regression models. R. denotes river and Crk. denotes creek. NLP, SLP, and UP refer to Michigan's Northern Lower Peninsula, Southern Lower Peninsula, and Upper Peninsula, respectively.

Stream	Map	Туре	Species	BFI	Area	Elevation
Au Sable R.	1	GD	BKC, BNT, RBT	0.72	5003.86	401.68
Bark R.*	2	RD	BNT	0.60	114.74	238.14
Bear Crk.*	3	GD	BNT	0.65	25.23	256.07
Black R.*	4	RD	BKC	0.55	1180.62	368.47
Boardman R.*	5	GD	BKC, BNT	0.63	626.78	319.63
Brule R.	6	RD	BNT	0.52	2719.49	515.46
Bryan Crk.*	7	RD	BKC	0.60	175.6	432.32
Canada Crk.*	8	RD	BKC	0.55	472.24	284.20
Carlton Crk.	9	GD	BKC	0.73	20.1	235.04
Carp R.*	10	RD	BKC, BNT, RBT	0.60	675.99	260.19
Cedar Crk.*	11	RD	BKC, BNT	0.50	48.17	267.04
Cedar R. (SLP)*	12	RD	RBT	0.60	114.74	336.84
Cedar R. (UP)	13	RD	BNT	0.60	735.56	306.49
Chocolay R.*	14	RD	RBT	0.56	404.04	379.63
Coldwater R.	15	RD	BNT	0.45	432.53	271.94
Cooks Run	16	RD	BKC, BNT	0.52	183.63	529.42
Davenport Crk.*	17	RD	RBT	0.57	20.12	250.71
Duke Crk.*	18	RD	BKC, BNT	0.50	85.73	276.93
E. Branch Fox R.*	19	GD	BKC, BNT	0.73	310.8	274.93
Elm R.*	20	RD	RBT	0.45	31.34	424.23
Escanaba R.*	21	RD	BKC, BNT	0.44	1012.69	424.08
Falls R.	22	RD	BKC	0.52	118.62	377.38
Hersey R.	23	GD	BNC	0.62	297.85	368.40
Iron R.*	24	RD	BKC	0.52	181.04	488.86
Little Indian R.*	25	GD	BKC	0.73	220.93	277.80
Little Muskegon R.	26	GD	RBT	0.62	966.07	313.04
Manistee R.*	27	GD	BKC, BNT, RBT	0.65	1916.59	406.05
Mann Crk.	28	GD	BKC	0.65	44.29	202.39
Martin Crk.	29	GD	BKC	0.61	52.84	259.35
Menominee R.	30	RD	RBT	0.57	10308.2	477.73

Stream	Map	Туре	Species	BFI	Area	Elevation
Miller Crk.	31	GD	BKC	0.65	2.8	241.26
Mosquito Crk .	32	GD	BKC	0.62	29.01	193.09
Muskegon R.	33	GD	RBT	0.62	6604.47	359.73
Ogontz R.	34	GD	RBT	0.74	53.16	214.53
Paint R.	35	RD	BNT	0.52	1613.56	496.64
Pere Marquette R.*	36	GD	BNT	0.61	1901.05	310.87
Pigeon R.*	37	GD	BNT, RBT	0.65	944.5	380.18
Pine R. (SLP)*	38	RD	BNT	0.49	1622.37	318.84
Pine R. (NLP)*	39	GD	BKC, BNT, RBT	0.65	688.94	395.08
Prairie Crk.*	40	RD	BNT	0.5	270.83	246.3
Rapid R.	41	GD	BKC, BNT, RBT	0.63	212.64	355.73
Rogue R.*	42	RD	BNT, RBT	0.5	678.58	278.19
Salmon Trout R.*	43	RD	BKC	0.45	104.12	442.89
Silver Crk.	44	GD	BKC	0.65	8	224.22
S. Branch Pine R.	45	GD	RBT	0.72	114.34	273.14
St. Joseph R.	46	GD	BKC, RBT	0.63	10722.6	346.56
Sturgeon R.	47	GD	BKC, RBT	0.74	505.05	276.66
Tahquamenon R.*	48	RD	BNT	0.55	2027.96	285.95
Tamarack Crk.	49	GD	BNT, RBT	0.62	375.55	302.21
W. Branch Maple R.	50	GD	BKC	0.65	598.29	282.57
W. Branch Sturgeon R.*	51	GD	BKC, BNT, RBT	0.65	473.97	394.9
Yellow Dog R.*	52	RD	RBT	0.52	178.71	537.07

TABLE 2.1 (cont'd).

Allen 1999; Kelleher et al. 2012) whereby daily streamflow records were partitioned into groundwater and surface-runoff components to determine the relative contribution of each. A BFI of 0.60 was treated as a threshold for streams to be categorized as groundwater-dominated (GD; BFI > 0.60) or surface runoff-dominated (RD; BFI \leq 0.60; McKergow et al. 2005; Dukić and Mihailović 2012).

Stream-specific regression models

Historical air and water temperatures were used to develop stream-specific temperature regression models (Table 2.2). Daily air temperatures measured in July from 1990 to 2010 were obtained using the United States Department of Energy Historical Climate Network (CDIAC 2016). Air temperature measurements were reported from the gauging station closest to each stream's headwaters, where MDNR gauges recorded daily stream temperatures in July from 1990 to 2010. July temperatures were used because this month is typically the warmest and most thermally stressful for salmonids in Michigan (Zorn et al. 2011) and likely to be the time period that will first impact salmonid thermal habitat quality and quantity in a changing climate. In July, temperatures are typically more suitable (i.e. cooler) for salmonids that live in GD, heavily forested headwater reaches of Michigan streams (Drake and Taylor 1996; Hayes et al. 1998), so emphasis was placed on these reaches with the understanding that if they become warmer, temperatures in downstream reaches will also generally increase. The National Hydrography Dataset Plus Version 1 (NHDPlusV1) and the Watershed Boundary Dataset (USEPA 2005) were used to identify each stream's sub-basin (8-digit Hydrologic Unit Code [HUC8]) and subwatershed (HUC 12). In addition, NHDPlusV1 and the United States Geological Survey StreamStats interactive map application (USGS 2015) were used to measure drainage area (km²)

Stream	Model	SE	F	Р	R^2
Runoff-dominated					
Bark R.	Water = $12.98 + 0.32*air$	0.05	49.41	< 0.01	0.86
Bryan Crk.	Water = $7.69 + 0.42$ *air	0.08	28.86	< 0.01	0.78
Carp R.	Water = 12.06 + 0.28*air	0.04	41.63	< 0.01	0.84
Cedar Crk.	Water = $6.32 + 0.56$ *air	0.09	39.10	< 0.01	0.83
Cedar R. (SLP)	Water = $11.42 + 0.25*air$	0.03	97.82	< 0.01	0.92
Elm R.	Water = $2.11 + 0.82$ *air	0.06	193.20	< 0.01	0.96
Escanaba R.	Water = $3.03 + 0.88$ *air	0.14	39.26	< 0.01	0.83
Pine R. (SLP)	Water = $9.23 + 0.40$ *air	0.04	119.15	< 0.01	0.94
Prairie Crk.	Water = $0.95 + 0.74$ *air	0.07	106.03	< 0.01	0.93
Salmon Trout R.	Water = $8.23 + 0.29$ *air	0.05	33.60	< 0.01	0.80
Tahquamenon R.	Water = 12.29 + 0.50*air	0.05	115.88	< 0.01	0.93
Groundwater-dominated					
Bear Crk.	Water = $11.61 + 0.23$ *air	0.03	46.74	< 0.01	0.85
Black R.	Water = $8.74 + 0.29$ *air	0.04	57.04	< 0.01	0.88
Boardman R.	Water = 11.99 + 0.14*air	0.02	72.85	< 0.01	0.90
Canada Crk.	Water = $6.91 + 0.60$ *air	0.08	61.72	< 0.01	0.88
Chocolay R.	Water = 10.29 + 0.23*air	0.03	77.99	< 0.01	0.91
Davenport Crk.	Water = $8.97 + 0.13$ *air	0.01	99.55	< 0.01	0.92
Duke Crk.	Water = $4.45 + 0.48$ *air	0.08	37.27	< 0.01	0.82
East Branch Fox R.	Water = $7.73 + 0.33$ *air	0.04	86.45	< 0.01	0.91
Iron R.	Water = $12.76 + 0.30$ *air	0.04	52.58	< 0.01	0.87
Little Indian R.	Water = $14.86 + 0.06$ *air	0.01	83.65	< 0.01	0.91
Manistee R.	Water = $10.67 + 0.13$ *air	0.02	57.70	< 0.01	0.88
Pere Marquette R.	Water = $12.50 + 0.18*air$	0.02	51.89	< 0.01	0.86
Pigeon R.	Water = 11.93 + 0.11*air	0.01	60.49	< 0.01	0.88
Pine R. (NLP)	Water = 10.89 + 0.22*air	0.03	73.41	< 0.01	0.90
Rogue R.	Water = 13.17 + 0.23*air	0.04	27.46	< 0.01	0.77
West Branch Sturgeon R.	Water = $11.93 + 0.06$ *air	0.01	67.49	< 0.01	0.89
Yellow Dog R.	Water = $9.90 + 0.38$ *air	0.06	45.58	< 0.01	0.85

TABLE 2.2. Stream-specific temperature regressions with standard errors (SE), *F* values (i.e. $F_{1,7}$), *P* values, and R^2 values. S and A denote stream temperature and air temperature, respectively. R. denotes river and Crk. denotes creek. SLP and NLP refer to Michigan's Southern Lower Peninsula and Northern Lower Peninsula, respectively.

and mean elevation (m) for each stream. Stream-specific regression models were developed by pairing mean July air and water temperatures from recent years (i.e. 2002–2010) for the 28 streams for which historical stream temperatures were available (Table 2.1, 2.2). To predict future stream temperatures, the product of air temperature regression coefficients and air temperature projections (described below) was calculated and added to model intercepts (i.e. stream temperature = air temperature coefficient*projected future air temperature + intercept). Air temperature coefficients represented indices of stream thermal sensitivity (i.e. relative susceptibility to temperature change) because larger positive coefficients produced warmer stream temperatures (Kelleher et al. 2012).

Generalized regression models

Stream temperatures were also predicted by converting sub-basin air temperature projections to water temperatures using two generalized regression equations. The Stefan and Preud'homme (1993, hereafter referred to as SP) model, developed specifically for RD streams, estimates weekly stream temperature by:

$$T_w = 2.9 + 0.86 T_a$$

where T_w is water temperature (° C) and T_a is air temperature (° C). The standard deviation (SD) of the model is 2.16° C.

The Krider et al. (2013, hereafter referred to as K) model, developed specifically for GD streams, estimates weekly stream temperature by:

 $T_w = 6.63 + 0.38 T_a$,

where T_w is water temperature (° C) and T_a is air temperature (° C). The model SD is 4.80° C.

The K model was used to project GD stream temperatures, whereas the SP model was used to predict RD stream temperatures, as these models were developed specifically for those corresponding streams types. Although both models were developed for weekly temperatures, daily and monthly air and water temperatures have been reported to be associated through a nearly 1:1 relationship (Ozaki et al. 2003), suggesting a strong positive weekly-to-monthly relationship and validating use of monthly average air temperatures to project stream temperatures.

Air temperature projections

Mean July air temperatures were forecasted in future years (2036 and 2056) for each subbasin evaluated. Air temperatures were projected using three coupled climate models: the Third Generation Coupled Global Climate Model (CGCM3, Canadian Centre for Climate Modelling and Analysis), the CM2 Global Coupled Climate Model (CM2, Geophysical Fluid Dynamics Laboratory at the National Oceanic and Atmospheric Administration), and the Hadley Centre Coupled Model version 3 (HadCM3, Met Office, United Kingdom's National Weather Service). All models were based on the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset and had variable thermal input parameters (e.g. solar radiation, volcanic activity, trace gases, sulfate aerosols). Spatial downscaling was performed using the Bias-Correction Spatial Disaggregation (BCSD) approach to adjust the resolution of the climate model (~200 km x 200 km) to a scale appropriate for Michigan streams (12 km x 12 km; Maurer et al. 2007). Mean July air temperatures were obtained for Michigan sub-basins containing salmonid streams from the United States Forest Service's (USFS) Eastern Forest Environmental Threat Assessment Center (EFETAC) in North Carolina. Temperatures were projected using the Special Report of Emission Scenarios A2 and B1 climate forcing scenarios and the CGCM3, CM2, and HadCM3 models using area-weighted means for all years. The A2 scenario (hereafter "high emissions") predicts atmospheric CO₂ concentrations to be 820 ppm in 2100 in a world characterized by rapid economic growth and efficient energy technologies (IPCC 2007). In contrast, the B1 scenario (hereafter "low emissions") projects atmospheric CO₂ concentrations to be 550 ppm in 2100 in a convergent world with a service and information economy and reduced material consumption (IPCC 2007).

Stream temperature and thermal habitat suitability projections

Stream-specific and generalized models were used to backcast July stream temperatures in 2006 and 2012 and forecast July temperatures in 2036 and 2056 based on air temperature predictions in these years. Backcasting was performed to evaluate the accuracy of streamspecific and generalized models by comparing predicted and actual temperatures in years with pre-existing stream temperature metrics. Mean air temperatures were calculated from the three CCM's to account for each model's uncertainty, unique temperature drivers (e.g. forest canopy density, atmospheric pressure, soil layering), and range of predicted air temperatures. Speciesspecific thermal habitat suitability statuses were assigned for each stream based on temperature thresholds for growth and survival associated with projected July temperatures. Status 1 streams had maximum July average temperatures that were optimal for growth of brook charr (11.0–16.5 ° C; Raleigh 1982a), brown trout (12.0–17.0° C; Raleigh et al. 1986; Hay and Young 2006), and rainbow trout (12.0–16.4° C; Wurtsbaugh and Davis 1977; Raleigh 1982b). Temperatures of status 2 streams resulted in reduced growth of brook charr (16.5–20.5° C; Raleigh 1982a), brown trout (17.0–20.0° C; Elliott and Hurley 2000), and rainbow trout (16.4–22.5° C; Wurtsbaugh and Davis 1977). Status 3 streams had temperatures that were too warm for growth to occur: 20.5–25.3° C for brook charr (Baldwin 1957; Raleigh 1982a), 20.0–26.2° C for brown trout (Hay and Young 2006), and 22.5–25.0° C for rainbow trout (Wurtsbaugh and Davis 1977; Raleigh 1982b). Finally, status 4 streams had thermal conditions that create high mortality risk for brook charr (>25.3° C; Fry et al. 1946; Raleigh 1982a), brown trout (>26.2° C; Hay and Young 2006), and rainbow trout (>25.0° C; Wurtsbaugh and Davis 1977; Raleigh 1982b).

Analyses

The accuracy of stream-specific regression models was evaluated by calculating the deviation between projected and actual stream temperatures and salmonid thermal habitat suitability statuses in 2006. Similarly, the accuracy of generalized regression models was assessed by calculating differences between projected and actual stream temperatures and salmonid thermal habitat suitability statuses. In comparing generalized K and SP models, temperature projections were considered inaccurate if they were lower (i.e. under-prediction) or higher (i.e. over-prediction) than actual temperatures by an amount greater than the standard deviation of the model with the lowest standard deviation (i.e. SP, $SD = 2.16^{\circ}$ C). The relative accuracy of stream-specific and generalized models was evaluated by comparing each model's deviation between projected and actual temperatures and salmonid thermal habitat suitability statuses with those of the corresponding model (i.e. generalized or stream-specific) in each of the 28 streams with historical water temperatures (Table 2.1). Stream-specific models could not be developed for the 24 streams (17 GD, 7 RD) for which historical water temperatures were not available. However, it was deemed appropriate to project stream temperatures and habitat suitability statuses using either the generalized K model (for the additional 17 GD streams) or the

SP model (for the additional 7 RD streams) if the accuracy of these models in predicting habitat suitability in their respective streams was greater than 80%. Temperature deviations (i.e. between actual temperatures and model projections and between stream-specific and generalized model predictions) were considered biologically significant if they produced changes in thermal habitat suitability statuses. Such changes were necessary for biological significance as defined in this manuscript, so temperature deviations rather than absolute temperatures were the appropriate measurement and were required for defining management-relevant categories for growth and survival.

To investigate the applicability of stream-specific and generalized models in regions outside Michigan, temperatures and thermal habitat suitability projections from the two model types were compared with historical (i.e. 2006) temperatures and habitat suitability statuses in five reported high-quality brook charr and brown trout streams located in the States of Connecticut, Maine, North Carolina, and Wisconsin, USA (Schlee 2014). Historical data for these streams were obtained from the United States Geological Survey National Water Information System (USGS 2016).

Results

Temperature projections

Stream-specific models projected historical water temperatures more accurately than generalized models in all 28 streams that had historical water temperatures available. In GD streams, the mean deviation of stream-specific model projections from actual temperatures in 2006 was -0.30° C (SD = 0.35, range = -0.71-0.79) under the high CO₂ emission scenario and -0.38° C (SD = 0.41, range = -1.04-0.79) under the low emission scenario. Compared to stream-

specific model predictions, the mean deviation of generalized K model projections in GD streams was larger under high emissions (-1.21° C, SD = 2.10, range = -5.40–2.60) and low emissions (-1.36° C, SD = 2.13, range = -5.60–2.30). Similarly, the mean deviation of streams specific model projections from actual temperatures in RD streams was -0.70° C (high emissions, SD = 0.77, range = -1.78–1.14)) and -0.88° C (low emissions; SD = 0.75, range = -1.70–0.84), compared to 2.57° C (high emissions, SD = 1.92, range = -0.70–5.30) and 2.10° C (low emissions, SD = 2.11, range = -1.50–4.60) for the generalized SP model. For streams in the State of Michigan, stream-specific models predicted that stream temperatures will increase by an average of 1.5° C (GD streams) and 3.1° C (RD streams) under high emissions and 1.2° C (GD streams) and 3.1° C (RD streams) under low emissions from 2016 to 2056. Throughout Michigan, generalized models projected stream temperatures will increase by an average of 0.6° C (GD streams) and 1.5° C (RD streams) under high emissions and 0.8° C (GD streams) and 1.9° C (RD streams) under high emissions and 0.8° C (GD streams) and 1.9° C (RD streams) under high emissions and 0.8° C (GD streams) and 1.9°

Thermal habitat suitability projections

Although stream-specific models predicted temperatures of GD and RD streams more accurately than generalized models, both model types projected accurate salmonid thermal habitat suitability statuses in GD streams (Figure 2.2). Under high and low CO₂ emissions, stream-specific models projected thermal habitat suitability with 100 % accuracy in GD streams with brook charr, brown trout, and rainbow trout (Table 2.3). Deviations between actual temperatures and stream-specific model projections were not biologically significant as they produced the same thermal habitat suitability statuses. In comparison, the overall accuracy of the generalized K model in projecting thermal habitat suitability was 82 % in GD streams for brook

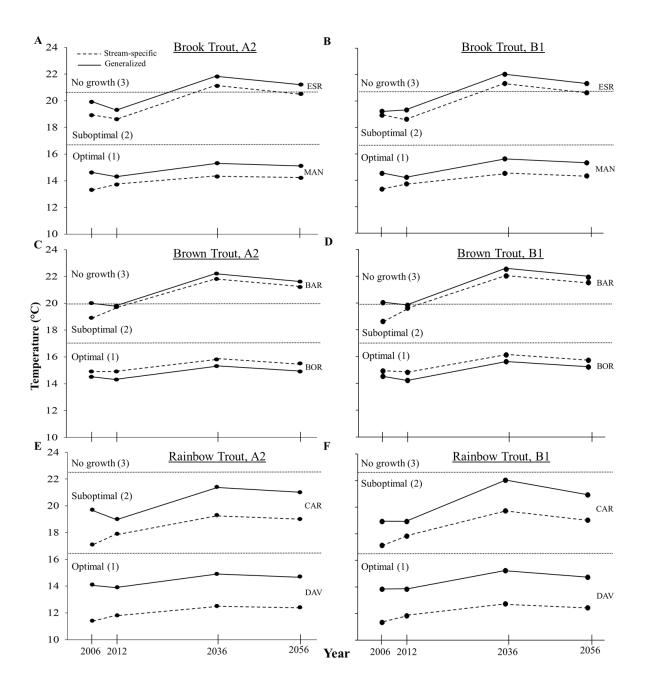


FIGURE 2.2. Temperature predictions in representative Michigan streams in 2006, 2012, 2036, and 2056 using stream-specific (dotted lines) and generalized (solid lines) temperature models. Plots are organized by species and emissions scenario: (a) brook charr, A2 scenario; (b) brook charr, B1 scenario; (c) brown trout, A2 scenario; (d) brown trout, B1 scenario; (e) rainbow trout, A2 scenario; (f) rainbow trout, B1 scenario. In each plot, the upper stream is surface runoff-dominated, and the lower stream is groundwater-dominated. Dotted lines represent transitions between thermal habitat suitability statuses. Stream abbreviations are as follows: BAR = Bark River, BOR = Boardman River, CAR = Carp River, DAV = Davenport Creek, ESR = Escanaba River, MAN = Manistee River.

TABLE 2.3. Projected temperatures (° C) and associated thermal habitat suitability (THS) statuses for growth and survival of brook charr (BKC), brown trout (BNT), rainbow trout (RBT), and all three species (All) in groundwater-dominated streams (1 = optimal, 2 = suboptimal, 3 = no growth, 4 = high mortality risk). Actual (i.e., field-measured) temperatures and THS statuses in 2006 are also included. Predictions are derived from stream-specific and generalized models (separated by commas) under the A2 carbon dioxide emissions scenario and are similar to those from the B1 scenario (not included here). R. denotes river, Crk. denotes creek, and NLP denotes the Northern Lower Peninsula of Michigan.

Stream	Species	Year	Temperature	THS	Actual	Actual THS
Bear Crk.	BNT	2006	16.5,15.4	1,1	15.8	1
		2012	16.7,15.1	1,1		
		2036	17.8,16.0	2,1		
		2056	18.2,16.2	2,1		
Black R.	BKC	2006	14.5,14.6	1,1	15.1	1
		2012	15.1,14.3	1,1		
		2036	16.3,15.3	1,1		
		2056	16.0,15.0	1,1		
Boardman R.	BKC, BNT	2006	14.9,14.5	1,1	15	1
		2012	14.9,14.3	1,1		
		2036	15.8,15.3	1,1		
		2056	15.5,14.9	1,1		
Canada Crk.	BKC	2006	19.4,14.6	2,1	20	2
		2012	19.5,14.3	2,1		
		2036	22.9,15.3	3,1		
		2056	21.9,15.0	3,1		
Duke Crk.	BKC, BNT	2006	14.7,15.3	1,1	15.3	1
		2012	15.8,14.9	1,1		
		2036	18.5,15.9	2,1		
		2056	19.1,16.0	2,1		
E. Branch Fox R.	BKC, BNT	2006	13.8,14.0	1,1	14.2	1
		2012	14.1,13.8	1,1		
		2036	15.6,14.8	1,1		
		2056	15.3,14.6	1,1		
Iron R.	BKC	2006	18.5,14.1	2,1	18.6	2
		2012	17.8,13.8	2,1		
		2036	19.7,15.0	2,1		
		2056	19.2,14.7	2,1		

Stream	Species	Year	Temperature	THS	Actual	Actual THS
Little Indian R.	BKC	2006	16.1,14.0	1,1	16.2	1
		2012	16.1,13.8	1,1		
		2036	16.5,14.8	2,1		
		2056	16.4,14.6	1,1		
Manistee R.	All	2006	13.3,14.6	1,1	13.6	1
		2012	13.7,14.3	1,1		
		2036	14.3,15.3	1,1		
		2056	14.2,15.1	1,1		
Pigeon R.	BNT, RBT	2006	14.1,14.4	1,1	14.5	1
		2012	14.2,14.2	1,1		
		2036	14.8,15.1	1,1		
		2056	14.6,14.8	1,1		
Pine R. (NLP)	All	2006	15.3,14.6	1,1	16	1
		2012	15.9,14.3	1,1		
		2036	17.1,15.3	2,1		
		2056	16.9,15.1	2,1		
Rogue R.	BNT, RBT	2006	18.0,15.3	2,1	18.4	2
		2012	17.9,14.9	2,1		
		2036	19.0,15.9	2,1		
		2056	19.2,16.0	2,1		
W. Branch Sturgeon R.	All	2006	13.1,14.4	1,1	13.3	1
		2012	13.2,14.2	1,1		
		2036	13.5,15.1	1,1		
		2056	13.4,14.8	1,1		
Yellow Dog R.	RBT	2006	17.3,14.1	2,1	18	2
		2012	19.7,13.9	2,1		
		2036	21.8,15.0	2,1		
		2056	21.3,14.8	2,1		

TABLE 2.3 (cont'd).

charr (80 % accuracy), brown trout (89 % accuracy), and rainbow trout (75 % accuracy; Table 2.3) under both emissions scenarios.

In contrast to GD streams, differences in temperature predictions between stream-specific and generalized models in RD systems were more often biologically significant (Figure 2.2). Stream-specific models were more accurate than generalized models in predicting salmonid thermal habitat suitability statuses in RD streams. Compared to 100 % accuracy in GD systems, stream-specific models predicted thermal habitat suitability with 80 % accuracy in RD streams for brook charr (80 % accuracy), brown trout (75 % accuracy), and rainbow trout (100 % accuracy; Table 2.4) under high CO₂ emissions. Under low emissions, stream-specific models predicted thermal habitat suitability with 93% accuracy in GD streams for brook charr (80 % accuracy), brown trout (100 % accuracy), and rainbow trout (100 % accuracy; Table 2.4). In comparison, under high emissions, the overall accuracy of the generalized SP model was 47 % in RD streams for brook charr (60 % accuracy), brown trout (25 % accuracy), and rainbow trout (100 % accuracy; Table 2.4). Under low emissions, the overall accuracy of the generalized SP model was 60 % in RD streams for brook charr (60 % accuracy), brown trout (50 % accuracy), and rainbow trout (100 % accuracy; Table 2.4).

Generalized K versus SP models

The generalized K model predicted stream temperatures more accurately than the generalized SP model. The generalized K model predicted historical GD stream temperatures with 75 % accuracy under high and low CO₂ emissions (Table 2.3), whereas the generalized SP model backcasted temperatures with only 36 % accuracy under high and low CO₂ emissions (Table 2.4). The generalized SP model over-predicted temperatures by 2.4–5.3° C (average

TABLE 2.4. Projected temperatures (° C) and associated thermal habitat suitability (THS) statuses for growth and survival of brook charr (BKC), brown trout (BNT), rainbow trout (RBT), and all three species (All) in surface runoff-dominated streams (1 = optimal, 2 = suboptimal, 3 = no growth, 4 = high mortality risk). Actual (i.e. field-measured) temperatures and THS statuses in 2006 are also included. Predictions are derived from stream-specific and generalized models (separated by commas) under the A2 carbon dioxide emissions scenario and are similar to those from the B1 scenario (not included here). R. denotes river, Crk. denotes creek, and SLP denotes the Southern Lower Peninsula of Michigan.

Stream	Species	Year	Temperature	THS	Actual	Actual THS
Bark R.	BNT	2006	18.9,20.4	2,3	19.9	2
		2012	19.7,19.8	2,2		
		2036	21.8,22.2	3,3		
		2056	21.2,21.6	3,3		
Bryan Crk.	BKC	2006	15.3,19.9	1,2	16.7	2
		2012	17.2,19.3	2,2		
		2036	19.9,21.8	2,3		
		2056	19.4,21.2	2,3		
Carp R.	All	2006	17.1,19.7	2,2	17.6	2
		2012	17.9,19.0	2,2		
		2036	19.3,21.4	2,3		
		2056	19.0,21.0	2,3		
Cedar Crk.	BKC, BNT	2006	18.3,22.5	2,3	18.3	2
		2012	18.7,21.7	2,3		
		2036	19.9,23.8	2,3		
		2056	20.1,24.2	2,3		
Cedar R. (SLP)	BNT	2006	16.6,20.4	1,3	17.1	2
		2012	16.0,19.8	1,2		
		2036	17.3,22.2	2,3		
		2056	16.9,21.6	1,3		
Escanaba R.	BKC, BNT	2006	18.9,19.9	2,2	19.9	2
		2012	18.6,19.3	2,2		
		2036	21.1,21.8	3,3		
		2056	20.5,21.2	3,3		
Elm R.	RBT	2006	17.0,19.9	2,2	17.5	2
		2012	20.7,19.4	2,2		
		2036	25.4,22.2	4,2		
		2056	24.3,21.5	3,2		

Stream	Species	Year	Temperature	THS	Actual	Actual THS
Pine R. (SLP)	BNT	2006	17.5,22.2	2,3	18.4	2
		2012	18.5,21.4	2,3		
		2036	20.5,23.6	3,3		
		2056	20.7,23.8	3,3		
Prairie Crk.	BNT	2006	16.6,22.5	1,3	18.3	2
		2012	17.9,21.7	2,3		
		2036	21.4,23.8	3,3		
		2056	22.0,24.2	3,3		
Salmon Trout R.	BKC	2006	13.5,19.9	1,2	14.6	1
		2012	15.9,19.4	1,2		
		2036	17.8,22.2	2,3		
		2056	17.3,21.5	2,3		
Tahquamenon R.	BNT	2006	21.2,19.3	3,2	20	3
		2012	21.6,18.7	3,2		
		2036	24.0,21.1	3,3		
		2056	23.6,20.7	3,3		

TABLE 2.4 (cont'd).

3.8°C) in seven RD streams (i.e. Bryan Creek, Cedar Creek, Cedar River, Elm River, Pine River, Prairie Creek, Salmon Trout River) under high emissions and by 2.5–4.6° C (average 3.7° C) in six RD streams (i.e. Bryan Creek, Cedar Creek, Cedar River, Pine River, Prairie Creek, Salmon Trout River) under low emissions (Table 2.4). The generalized SP model predicted thermal habitat suitability in RD streams with 35 % lower accuracy (high emissions) and 22 % lower accuracy (low emissions) than the generalized K model in GD systems. Therefore, generalized models are best suited for use in GD streams.

Data-limited streams

Because the generalized K model projected historical thermal habitat suitability statuses in GD streams with relatively high accuracy (> 80 %), the K model was used to predict temperature and habitat suitability in the 17 GD systems for which historical water temperatures were unavailable. Under both high and low CO_2 emissions, all of these streams were projected to maintain optimal growing conditions in July for brook charr, brown trout, and rainbow trout until the year 2056 (Table 2.5).

Model applicability to streams outside Michigan

Thermal habitat suitability projections from stream-specific and generalized models were compared with historical habitat suitability statuses in five streams outside the State of Michigan to gauge the applicability of the two model types in different regions of the USA. For these streams, generalized models predicted salmonid thermal habitat suitability with comparable accuracy to stream-specific models. In five brook charr streams, 67 % of generalized model predictions were accurate, compared to 0 % of stream-specific model predictions (Table 2.6).

TABLE 2.5. List of groundwater-dominated streams without actual (i.e. field-measured) 2006 stream temperatures for which generalized models were used to predict temperatures and associated associated thermal habitat suitability (THS) statuses in 2006, 2012, 2036, and 2056 under A2 and B1 emissions (separated by commas). 1 = optimal, 2 = suboptimal, 3 = no growth, 4 = high mortality risk. R. denotes river and Crk. denotes creek. Species abbreviations are as follows: ALL = brook charr, brown trout, and rainbow trout; BKC = brook charr; BNT = brown trout; RBT = rainbow trout.

Stream	2006 Pr	THS	2012 Pr	THS	2036 Pr	THS	2056 Pr	THS
Au Sable R.	14.6,14.4	ALL: 1,1	14.2,14.1	ALL: 1,1	15.2,15.5	ALL: 1,1	14.9,15.1	ALL: 1,1
Carlton Crk.	14.0,13.7	BKC: 1,1	13.8,13.8	BKC: 1,1	14.8,15.1	BKC: 1,1	14.6,14.6	BKC: 1,1
Hersey R.	14.7,14.7	BNT: 1,1	14.4,14.4	BNT: 1,1	15.3,15.7	BNT: 1,1	15.3,15.3	BNT: 1,1
Little Muskegon R.	14.7,14.7	RBT: 1,1	14.4,14.4	RBT: 1,1	15.3,15.7	RBT: 1,1	15.3,15.4	RBT: 1,1
Mann Crk.	15.4,15.4	BKC: 1,1	15.1,15.1	BKC: 1,1	16.0,16.3	BKC: 1,1	16.2,16.2	BKC: 1,1
Martin Crk.	14.9,14.9	BKC: 1,1	14.6,14.6	BKC: 1,1	15.5,15.8	BKC: 1,1	15.5,15.6	BKC: 1,1
Miller Crk.	15.4,15.4	BKC: 1,1	15.1,15.1	BKC: 1,1	16.0,16.3	BKC: 1,1	16.2,16.2	BKC: 1,1
Mosquito Crk.	14.7,14.7	BKC: 1,1	14.4,14.4	BKC: 1,1	15.3,15.7	BKC: 1,1	15.3,15.4	BKC: 1,1
Muskegon R.	14.7,14.7	RBT: 1,1	14.4,14.4	RBT: 1,1	15.3,15.7	RBT: 1,1	15.3,15.4	RBT: 1,1
Ogontz R.	14.1,13.9	RBT: 1,1	13.9,13.9	RBT: 1,1	14.9,15.2	RBT: 1,1	14.7,14.7	RBT: 1,1
Rapid R.	14.5,14.5	ALL: 1,1	14.3,14.2	ALL: 1,1	15.3,15.6	ALL: 1,1	14.9,15.2	ALL: 1,1
S. Branch Pine R.	14.6,14.4	RBT: 1,1	14.2,14.1	RBT: 1,1	15.2,15.5	RBT: 1,1	14.9,15.1	RBT: 1,1
Silver Crk.	15.4,15.4	BKC: 1,1	15.1,15.1	BKC: 1,1	16.0,16.3	BKC: 1,1	16.2,16.2	BKC: 1,1
St. Joseph R.	15.6,15.5	BKC: 1,1	15.2,15.2	BKC: 1,1	16.0,16.4	BKC: 1,1	16.4,16.5	BKC: 1,2
		RBT: 1,1		RBT: 1,1		RBT: 1,1		RBT: 2,2
Sturgeon R.	14.1,13.9	BKC: 1,1	13.9,13.9	BKC: 1,1	14.9,15.2	BKC: 1,1	14.7,14.7	BKC: 1,1
		RBT: 1,1		RBT: 1,1		RBT: 1,1		RBT: 1,1
Tamarack Crk.	14.7,14.7	BNT: 1,1	14.4,14.4	BNT: 1,1	15.3,15.7	BNT: 1,1	15.3,15.4	BNT: 1,1
		RBT: 1,1		RBT: 1,1		RBT: 1,1		RBT: 1,1
W. Branch Maple R.	14.4,14.3	BKC: 1,1	14.2,14.0	BKC: 1,1	15.1,15.5	BKC: 1,1	14.8,15.1	BKC: 1,1

TABLE 2.6. List of brook charr (BKC) and brown trout (BNT) streams located outside Michigan with actual temperatures (i.e., fieldmeasured in 2006) and associated thermal habitat suitability (THS) statuses. 2 = suboptimal, 3 = no growth, 4 = high mortality risk. The table also includes projected temperatures (stream-specific [SS] model, generalized [Gen] model) and associated THS statuses in 2006. State abbreviations are as follows: Connecticut (CT), Maine (ME), North Carolina (NC), Wisconsin (WI).

Stream	Actual	BKT THS	BNT THS	SS	Gen	BKT THS	BNT THS
Broad Swamp Brook, CT				24.9	21.8	3,3	3,3
Meduxnekeag River, ME	19.6	2	2	19.8	18.4	2,2	2,2
Deep Creek, NC	26.1	4	3	24.1	23.6	3,3	3,3
Embarrass River, WI	19.7	2	2	21.3	20.2	3,2	3,3
Red River, WI				21.1	20.2	3,2	3,3

Thermal habitat suitability projections were consistent between generalized and stream-specific models in three of five brook charr streams. In five brown trout streams outside Michigan, 67 % of generalized and stream-specific model predictions were accurate, and thermal habitat suitability projections were consistent between model types in all five streams (Table 2.6). The accuracy of generalized model thermal habitat suitability predictions was similar in streams outside and inside Michigan. At least two thirds of predictions were accurate in brook charr streams (outside Michigan: 67 % accuracy; inside Michigan: 73 % accuracy) and brown trout streams (outside Michigan: 67 % accuracy; inside Michigan: 71 % accuracy). The relatively high accuracy of generalized models in predicting thermal habitat suitability in streams within and outside Michigan indicates their applicability in coldwater fisheries management programs in the eastern and north central United States of America.

Discussion

Salmonids are ecologically, socioeconomically, and culturally important throughout the world. However, their comparatively low thermal optima (Raleigh 1982a, b; Raleigh et al. 1986) combined with global climate warming and widespread scarcity in long-term stream temperature data indicate a pressing need for reliable, cost-effective methods for projecting stream temperatures with limited data to manage thermal habitats. Although heat budget models represent a highly accurate method for predicting stream temperatures, they are expensive, data-intensive, and require physical, hydrological, and meteorological measurements at small spatial extents (e.g. stream reaches; Mohseni et al. 1998; Benyahya et al. 2007), which most fisheries management agencies do not have the resources to collect or analyze. As a result, fisheries

management agencies need efficient, cost-effective alternatives to accurately project future thermal habitat conditions.

This study demonstrates the utility of stream-specific and generalized temperature models for salmonid management amidst global climate change and resource limitations. This study shows that stream-specific models, reflecting the unique influence of thermal drivers in each system (e.g. air temperature, solar radiation, riparian shading, groundwater input, discharge, precipitation, evaporation; Bartholow 1989; Gu et al. 1998), predict temperatures more accurately than generalized, region-specific models. However, developing temperature profiles for stream-specific models requires considerable investments of funding, time, and personnel (e.g. purchase, installation, and monitoring of temperature gauges for each stream). Despite the higher accuracy of stream-specific models for prediction of stream temperatures in this study, generalized models were comparably accurate in projecting thermal habitat suitability for salmonid growth and survival in GD streams. Consequently, generalized models can be useful for fisheries professionals seeking to optimize the expenditure of finite resources on research and management efforts necessary to conserve coldwater stream fisheries with climate change.

The magnitude of stream warming projected in this study is similar to previous investigations conducted in and near the study area in Michigan. Water temperatures were predicted to increase by 0.1–3.8° C in GD streams and 0.2–6.8° C in RD streams in Michigan due to projected climate change from 2016 to 2056. These results corroborate projected stream temperature warming in other Upper Midwestern states (0.3–6.9° C in the State of Minnesota, USA: Pilgrim et al. 1998; 0.8–4.0° C in the State of Wisconsin, USA: Lyons et al. 2010). Previous research in Michigan indicates that GD streams are more thermally resilient than RD streams due to groundwater-driven thermal buffering and flow stability, which causes coldwater

fishes to be more susceptible to summer growth reductions in RD systems (Zorn et al. 2012). The present study supports this finding as the magnitude of temperature warming was projected to be greater in RD streams than GD systems with thermal buffering.

Generalized temperature models accurately projected stream thermal dynamics in GD streams within and outside Michigan, indicating their broad utility for salmonid management in other regions of the world with coldwater streams vulnerable to climate-induced warming. Generalized models projected thermal habitat suitability with 82 % accuracy in GD Michigan streams and were as accurate as stream-specific models in predicting thermal habitat suitability in systems outside Michigan. This indicates that generalized models are useful for forecasting temperature ranges for salmonid growth and survival in broad regions of the eastern and north central USA and suggests that generalized models are widely applicable in other regions that contain stream salmonid populations.

These findings are important for stream salmonid management because by using generalized models, fisheries professionals can invest fewer resources (e.g. funding, time, personnel) to achieve a comparable level of accuracy in projecting thermal conditions for salmonid growth and survival and may then invest more in implementing programs that enhance the thermal resilience of streams that are likely to be impacted by a warming environment. In addition, generalized models applied on regional scales would promote salmonid management strategies (e.g. harvest regulations) that, by virtue of their regional scale, would be would be more practical for fisheries stakeholders compared to the complex assortment of site-specific regulations that would result from using stream-specific models. Moreover, fisheries professionals can use generalized models as simple tools to inform anglers and other stakeholders about probable effects of climate change on coldwater stream fish communities,

including reduced salmonid abundance and increased abundance of warmwater fishes (e.g. centrarchids; Pease and Paukert 2014). Compared to stream-specific models, generalized models could be efficiently incorporated into existing regional-level stream salmonid management programs in the States of Michigan (Anonymous 2000), Wisconsin (WDNR 2002), Minnesota (MNDNR 2011), and elsewhere throughout the world (e.g. Spain; Antunes et al. 1999). Facing cost-benefit tradeoffs, fisheries professionals may willingly exchange the lower accuracy of generalized models in predicting temperature for their cost-effectiveness and efficiency, particularly their ability to project thermal habitat suitability with comparable accuracy and lower resource expenditure relative to stream-specific models.

Results from this study have other important implications for stream salmonid management throughout the world. As climate change increases air temperatures and decreases stream thermal habitat suitability for salmonid growth, reproduction, and survival (Lyons et al. 2010; Isaak et al. 2012), managing streams and their salmonid populations for thermal resilience will become an ever important task for fisheries professionals. This study indicates that by using generalized models, fisheries professionals can reduce costs associated with temperature modeling in GD streams and may then be able to allocate more resources toward thermal habitat management. Potential management actions include protecting riparian vegetation that provides shading (Blann et al. 2002), preserving grasslands and other land cover types that promote groundwater recharge (Siitari et al. 2011), and maintaining longitudinal stream connectivity that allows salmonids to move to cooler habitats (e.g. headwater reaches; Waco and Taylor 2010) during the warm summer months.

Generalized models are advantageous for watershed-level salmonid management as they enable relatively accurate, cost-effective stream temperature forecasting at regional scales.

Fisheries professionals can use results from generalized models to develop climate vulnerability maps that facilitate prioritization of streams for thermal habitat management in a changing climate. In addition, fisheries professionals can integrate generalized model temperature projections with socioeconomic information (e.g. angler values and behaviors, stream-specific resource availability) to design decision-support tools (DSTs) that streamline decision-making for stream salmonid management. As the applications of DSTs continue to be discovered (Azadivar et al. 2009, Bitunjac et al. 2016), they have proven to be important for ecologically, sociologically informed fisheries management in a changing climate (Lynch et al. 2015; Lynch et al. 2016). Accurate, readily interpretable generalized models can enable fisheries professionals to collaborate with policy makers to ensure that stream temperature modeling is used to inform the development of policies that sustain stream salmonid populations amidst predicted changes in the world's climate.

This study provides a foundation for future coldwater fisheries research throughout the world regarding the effects of increased air and water temperatures on stream salmonid populations and approaches to mitigate – and adapt to – the impacts of global climate change. Although this study focused on relatively data-rich streams in Michigan, Wisconsin, and the eastern United States, it employed methods for developing and comparing stream-specific and generalized stream temperature models that are widely applicable in other regions of the world. Stream temperature data spanning multiple years are necessary for using the methods described herein, thus we encourage fisheries professionals to expand the spatial and temporal coverage of air and stream temperature monitoring networks and thereby enhance their utility for fisheries management. Increased temperature data collection and installation of air and stream temperature gauging stations will enable comparisons between the present study and research conducted in

the western United States, Canada, Europe, and other regions of the world where stream salmonids are abundant yet stream-specific and generalized temperature models have not been juxtaposed. In addition to stream temperature modeling and thermal habitat management, further research is needed to assess other potential tools for sustaining stream salmonid populations and other species amidst climate change. For instance, the effects of management actions to restore stream habitat connectivity (e.g. dam removal, fish ladder installation at roadside crossings and culverts) on salmonid populations need to be more comprehensively assessed. Further research is needed to determine whether maintaining a diversity of salmonid genetic stocks, size classes, and prey species that tolerate temperatures projected under climate change (Hansen et al. 2015) is a useful strategy to increase the resilience of stream salmonid populations.

The goal of this study was to construct and compare stream-specific and generalized temperature models for Michigan streams to project future thermal habitat conditions (i.e. suitability statuses) for salmonid growth and survival, develop a model comparison approach that is spatially and temporally robust and broadly applicable within and beyond Michigan, and thereby inform salmonid management throughout the world amidst climate change and resource limitations. Our purpose was not to assess model performance in terms of absolute temperatures. Fisheries managers in Michigan and other regions with coldwater salmonid streams are primarily concerned with maintaining and/or improving thermal habitat conditions for salmonid growth and survival rather than evaluating model performance in terms of absolute temperatures. In these management systems, models assessing and comparing thermal habitat suitability statuses for growth and survival are more useful than those looking at absolute temperature. We structured the present manuscript correspondingly and believe a thermal habitat suitability approach is most appropriate for communicating with fisheries managers and other decision-

makers who are principally concerned with thermal habitat conditions. These individuals are not temperature modelers *per se* but rather decision-makers who require information on current and future thermal habitat conditions. However, we acknowledge that other fisheries management systems throughout the world operate differently and may require distinct thermal modeling approaches, including absolute temperature assessment, that reflect unique research goals and objectives.

In summary, this study demonstrates the efficacy of generalized temperature models for stream salmonid management in a changing climate, particularly in GD streams. In RD systems, the lower accuracy of generalized models than stream-specific models in predicting water temperature was often biologically significant, leading to differences in projected thermal habitat suitability statuses between model types. This suggests that fisheries professionals can reserve stream-specific models for systems in which the accuracy of temperature prediction is especially important, including streams that support trophy fishing opportunities, threatened/endangered species, or other ecologically or socioeconomically valuable resources. In these streams, the added costs of using stream-specific models and installing additional air and stream temperature monitoring stations may be justifiable for fisheries management agencies, given that these systems are especially valuable. In regions that contain both GD and RD streams, integrating generalized and stream-specific models will be an effective strategy for balancing model accuracy and efficiency. Overall, this study illustrates how fisheries professionals throughout the world can use different temperature modeling frameworks to optimize the expenditure of finite resources as they project future stream thermal conditions and develop more effective strategies for coldwater fisheries management amidst global climate change.

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CHAPTER 3: SCIENCE TO ACTION: DECISION-SUPPORT TO ADVANCE STREAM TROUT MANAGEMENT IN A CHANGING CLIMATE

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Abstract

Decision-making with limited information is commonplace in fisheries management, stemming from the need to sustain fisheries ecosystems in the face of changing environmental and human conditions. Decision support tools (DSTs) facilitate decision-making by systematically integrating environmental and socioeconomic information and accounting for variability in human and natural systems, yet they have not been widely applied in freshwater recreational fisheries management. As such, we collaborated with fisheries research and management professionals to develop a DST – specifically, a stream prioritization tool (SPT) – to inform fisheries management amid climate change in Michigan coldwater streams inhabited Brook Trout Salvelinus fontinalis, Brown Trout Salmo trutta, and Rainbow Trout Oncorhynchus *mykiss*. The SPT ranked streams by synthesizing management decision-making criteria that affect trout thermal habitat quality (e.g., current and future stream temperature, trout abundance, groundwater input). Productive, socioeconomically important trout streams with high thermal habitat quality such as the Au Sable and Manistee rivers were predictably the highest-ranked streams by the SPT and thus warrant continued trout population and thermal habitat management (e.g., groundwater conservation). However, certain streams currently important for recreational fishing (e.g., Muskegon River, Pere Marquette River) were projected to have relatively low thermal habitat quality by 2056, whereas other streams without top-tier fisheries (e.g., Rapid River, Davenport Creek) were predicted to have high-quality thermal habitats, suggesting they merit increased management efforts. Revealing unexpected yet management-relevant findings under different scenarios of climate change, the SPT is a flexible instrument to help sustain thermally resilient trout populations and streamline fisheries management decision-making amid climate change.

Introduction

The complexity and variability of coupled human and natural systems (CHANS) such as fisheries complicates their investigation and management by generating uncertainty about system dynamics (Liu et al. 2007). For example, the intricate interactions among fishes, fish habitats, and fisheries stakeholders often compel managers to make decisions with incomplete current and future knowledge of fisheries ecology (e.g., population size, habitat use) or human dimensions (e.g., stakeholder values, behavior, demographics). As climate change, invasive species, habitat alteration, and other stressors continue to increase the complexity and uncertainty of fisheries management (Hansen et al. 2015), it is important to develop approaches and tools that enable managers and allied stakeholders to make efficient, effective decisions to enhance fisheries sustainability. Decision support tools (DSTs) – broadly defined as information systems that organizations and individuals use to make informed decisions – can facilitate fisheries decision-making amid uncertainty by allowing information synthesis (e.g., biological, social, economic, political) and evaluation of trade-offs among different choices that fisheries professionals face (NRC 2010), thereby streamlining fisheries management.

The complexity of fisheries as CHANS demands that fisheries professionals and stakeholders make decisions by integrating biological, social, economic, and political information to manage and conserve fisheries. Informed decision-making using biological information requires that fisheries professionals consider the abundance, growth, and diversity of fish populations and their habitats – and threats they face – to make policy and management choices that enhance fisheries productivity and sustainability. Socially, evaluation of networks among professionals and stakeholders (e.g., policy makers, fishers, general public) and the ethics, values, and norms that influence these networks is necessary for socially informed

management of fisheries as CHANS (Ward et al. 2016; Arlinghaus et al. 2017). Commercial, recreational, and artisanal fisheries also support markets and economies spanning local to international scales, thus decision-making has a profound impact on individuals' livelihoods and quality of life and the well-being of entire communities and nations (Fréon et al. 2014; Carlson et al. 2017a, 2017b). Finally, fisheries are generally managed by government agencies (e.g., state, federal) whose decisions are influenced to varying degrees by government structure, the timescale of political appointments, and associated political conditions (Lynch et al. 2015). With such complex, multidimensional factors to consider, fisheries professionals would benefit from using DSTs that systematically and efficiently integrate biological, social, economic, and political information to facilitate management decision-making.

Fisheries decision support is a nascent field (Lynch et al. 2015) due to a historical research emphasis on the biology and ecology of fishes and their habitats as opposed to their integration with human dimensions that impact the societal value of fisheries. However, extant fisheries DSTs demonstrate the value of these tools for systematically informing integrated decision-making processes. For instance, Dichmont et al. (2013) developed a DST to aid Northern Prawn *Pandalus borealis* managers in selecting spatial closure strategies for Marine Protected Areas (MPAs) that optimized the attainment of socioeconomic and ecological objectives (e.g., consistent revenue for fishers, productive fish stocks). Likewise, Stortini et al. (2015) designed a DST to allow fisheries managers to visualize options for setting no-take boundaries to maximize fishery sustainability while minimizing socioeconomic costs to fishers in the St. Anns Bank MPA, Scotian Shelf, Canada. Although they have not been broadly applied in fisheries management, particularly in freshwater systems, DSTs have numerous applications with the potential to inform and advance inland fisheries management programs. Not only do

they synthesize ecological, economic, social, and political information to promote robust decisions, DSTs are compatible with structured decision-making, adaptive management, and related frameworks being used or proposed for use in fisheries management systems (Lynch et al. 2015). As a result, fisheries professionals can use DSTs to model diverse environmental and socioeconomic conditions and complement extant decision-making approaches to make better informed policy and management choices.

Fisheries decision support is particularly important amid climate change, a complex issue with diverse (and often uncertain) ecological, social, and political consequences that are affecting fisheries productivity at multiple scales. On an individual level, climate change can decrease fish growth and survival by increasing cortisol levels and reduce aerobic scope by depleting dissolved oxygen levels (Whitney et al. 2016). Warmwater fishes, particularly those in families Cyprinidae, Catostomidae, Ictaluridae, Centrarchidae, and Percidae that require warm temperatures for individual and population persistence (Lyons 1996; Lyons et al. 2009), may experience physiological benefits (e.g., higher reproductive success) resulting from warmer water temperatures. However, climate change is projected to decrease the recruitment, growth, abundance, and distribution of coldwater fishes – those in families Salmonidae and Cottidae with temperature preferenda ≤ 20 °C and critical thermal maxima ≤ 31 °C (Raleigh 1982a, 1982b; Raleigh et al. 1986; Lyons et al. 2009; Carlson et al. 2017c). As such, climate change will also impact fisheries stakeholders (e.g., fisheries professionals, commercial and recreational fishers) by altering fish abundance, growth, and distribution, which may interfere with stakeholders' ability to catch, eat, research, and manage fish (Hunt et al. 2016).

Given these multi-scale effects of climate change on fisheries, adaptation strategies should focus on enhancing the social-ecological resilience of fisheries ecosystems and human systems (i.e., their ability to retain structure and function amid climate change; Holling 1973; Paukert et al. 2016). Such resilience-based management will require collaboration among scientists, managers, biologists, policy makers, and public stakeholders within and outside the fisheries discipline whose decisions – individual or organizational – affect the viability and productivity of fish populations and their habitats (Carlson et al. 2017c). By integrating ecological, social, economic, and political information and providing a platform for multidisciplinary teamwork, DSTs facilitate fisheries decision-making that builds socialecological resilience.

The goal of this study was to develop a DST – specifically, a stream prioritization tool (SPT) – to rank coldwater streams based on to management decision-making criteria that affect trout thermal habitat quality (e.g., current and future stream temperature, relative abundance of trout, groundwater input). In turn, fisheries professionals can use the SPT to plan management programs that promote thermally resilient streams and sustain socio-ecologically valuable Michigan stream trout populations (i.e., Brook Trout Salvelinus fontinalis, Brown Trout Salmo trutta, Rainbow Trout Oncorhynchus mykiss; USFWS 2011) amid climate change. These species were selected because they are ecologically and recreationally important and widely distributed throughout Michigan (Zorn et al. 2011, 2012), making them effective indicator species for assessing the impacts of climatic warming on coldwater stream organisms (Carlson et al. 2017b). Our objectives were to: 1) forecast effects of air temperature warming due to climate change on future stream temperatures and thermal habitat suitability for trout growth and survival; 2) survey Michigan fisheries professionals regarding their perspectives about climate change effects on stream trout populations, coldwater habitats, fisheries management, and associated decisionmaking; and, 3) evaluate the perceptions of fisheries professionals regarding SPT development

(e.g., important management issues and decisions) and design (e.g., effective ways to create and deliver an SPT). We then used these results to develop an SPT to support Michigan fisheries professionals as they make decisions for resilience-based salmonid management amid climate change.

Methods

Study area

Michigan was an ideal study area in which to develop an SPT for coldwater fisheries management, as Brook Trout, Brown Trout, and Rainbow Trout are distributed throughout 31,000 km of streams (Godby et al. 2007; Tyler and Rutherford 2007) and support productive recreational fisheries in which more than 585,000 anglers spent 8.2 million angling days in 2011 (USFWS 2011). In addition, Michigan trout streams were important to study as coldwater stream temperatures throughout the Midwestern United States are projected to increase by 0.8–4.0 °C amid air temperature warming, with potentially effects on trout growth, reproduction, and survival (Pilgrim et al. 1998; Lyons et al. 2010).

Latitudinal location, hydrology (i.e., groundwater/surface-runoff dominance), and recreational importance were used as criteria for selecting 52 streams throughout the State of Michigan for this study (Figure 3.1). Streams were selected across a latitudinal thermal gradient spanning the State of Michigan from north to south to reflect the existing and projected variation in average air temperature amid climate change. Streams were also selected to encompass a hydrological gradient (i.e., groundwater dominance to surface-runoff dominance) over which Brook Trout, Brown Trout, and Rainbow Trout occur in Michigan. Moreover, all streams had

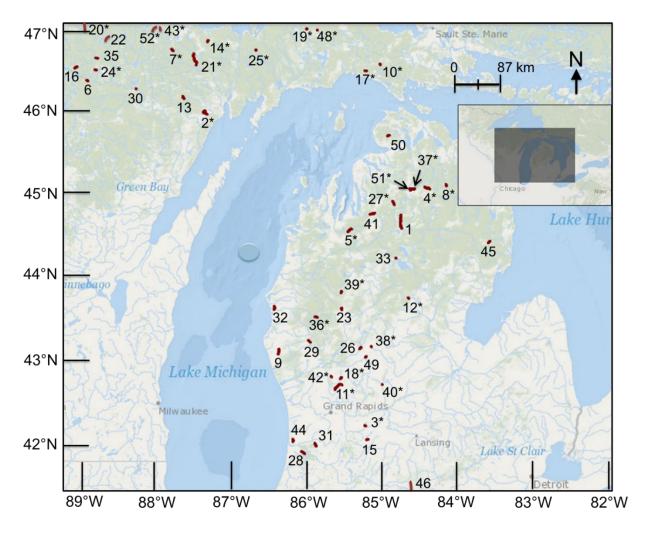


FIGURE 3.1. Map of 52 Brook Trout, Brown Trout, and Rainbow Trout streams in Michigan, USA. The map was produced using the stream prioritization tool described herein. Map numbers refer to individual streams: Au Sable R. (1), Bark R. (2*), Bear Creek (3*), Black R. (4*), Boardman R. (5*), Brule R. (6), Bryan Creek (7*), Canada Creek (8*), Carlton Creek (9), Carp R. (10*), Cedar Creek (11*), Cedar R. (12*), Cedar R. (13), Chocolay R. (14*), Coldwater R. (15), Cooks Run (16), Davenport Creek (17*), Duke Creek (18*), East Branch Fox R. (19*), Elm R. (20*), Escanaba R. (21*), Falls R. (22), Hersey R. (23), Iron R. (24*), Little Indian R. (25*), Little Muskegon R. (26), Manistee R. (27*), Mann Creek (28), Martin Creek (29), Menominee R. (30), Miller Creek (31), Mosquito Creek (32), Muskegon R. (33), Ogontz R. (34), Paint R. (35), Pere Marquette R. (36*), Pigeon R. (37*), Pine R. (38*), Pine R. (39*), Prairie Creek (40*), Rapid R. (41), Rogue R. (42*), Salmon Trout R. (43*), Silver Creek (44), South Branch Pine R. (45), St. Joseph R. (46), Sturgeon R. (47), Tahquamenon R. (48*), Tamarack Creek (49), West Branch Maple R. (50), W. Branch Sturgeon R. (51*), Yellow Dog R. (52*). Asterisks indicate that streams had historical field-collected air and stream temperatures for development of stream-specific regression models.

recreational fisheries for one or more of these species, making them important for fisheries professionals with the Michigan Department of Natural Resources (MDNR).

Fisheries professional survey

In its 2013–2017 Fisheries Division Strategic Plan (MDNR 2013), the MDNR explicitly identified the need for DSTs and described their value for optimizing fisheries management programs, which provided justification and enthusiasm for the fisheries professional survey and SPT developed herein. Fisheries managers and biologists employed by the MDNR were surveyed to evaluate their opinions and perspectives regarding management of Brook Trout, Brown Trout, and Rainbow Trout in Michigan given the threat of a warming climate. A 30question survey instrument approved by the Michigan State University Institutional Review Board (IRB # x16-1438e; i052807) was designed using SurveyMonkey® and emailed to 40 fisheries professionals (23% of MDNR fisheries workforce) encompassing all fisheries management offices throughout the state of Michigan. Reminder emails were sent every two to three weeks during a 2.5-month time span from November 2016 to February 2017 in which the survey was open. In total, 31 fisheries professionals responded to the survey, for a response rate of 78%. The survey encompassed a range of questions designed to assess the perspectives of fisheries professionals regarding current stream trout management strategies in Michigan; how resource availability (e.g., money, time, personnel) and thermal, hydrological, and biological conditions influence the management strategies they select (e.g., stocking, habitat protection/rehabilitation); and their perspectives regarding the essential components of an SPT to inform resilience-based salmonid management. Fisheries professionals were also asked to rank the relative importance of SPT criteria for evaluating and ultimately prioritizing streams for

current and future resilience-based management actions. These criteria included six factors that regulate thermal habitat quality and resilience amid climate change (Siitari et al. 2011, Carlson et al. 2017b,c): stream temperature, trout population characteristics (i.e., presence/absence, relative abundance), groundwater contribution, high-quality watershed land cover, high-quality riparian land cover, and projected changes in stream temperature resulting from climate change (Table 3.1, Figure 3.2). Four land cover types typically associated with optimal or near-optimal trout habitats were used to define the "high-quality" watershed and riparian land cover SPT criteria: deciduous forest, evergreen forest, mixed forest, and grassland (Siitari et al. 2011; Carlson et al. 2016). Criteria rankings were then used to calculate criterion-specific weights (i.e., relative importance values) for incorporation into the SPT (Table 3.1). Survey questions were designed in consultation with communications and survey specialists from the MDNR and Michigan State University to ensure that they were succinct, yet detailed enough to provide necessary information for stream trout management and SPT development.

Stream temperature

Daily water temperatures for all 52 streams studied herein were obtained from an MDNR database that contained temperature records from multiple reaches within each stream from 1990 to 2010. The temperature gauge closest to each stream's headwaters (i.e., farthest upstream) was selected because these reaches are generally coolest and most optimal for Michigan trout in summer (Drake and Taylor 1996; Hayes et al. 1998). As such, headwaters were the focus of this study because if their temperatures increase, temperatures in downstream temperatures in downstream reaches will also generally rise. The National Anthropogenic Barrier Dataset (Ostroff et al. 2013) was used to locate and omit stream temperature gauges directly below dams,

TABLE 3.1. Stream prioritization tool criteria and associated variables, data sources, and weights (i.e., relative importance values) for evaluating and prioritizing streams for fisheries management according to trout population and thermal habitat quality. Abbreviations are as follows: MDNR (Michigan Department of Natural Resources), USGS (United States Geological Survey), and NLCD (National Land Cover Database).

Criterion	Variable(s)	Source	Weight
Water temperature	Temperature (°C)	MDNR	0.23
Trout population characteristics	Presence/absence, catch-per-unit-effort (# fish/mile)	MDNR	0.20
Groundwater contribution	Base flow index	USGS, Neff et al. (2005)	0.17
High-quality watershed land cover	% deciduous/evergreen/mixed forest and grassland in watershed	NLCD 2011 (Homer et al. 2015)	0.14
High-quality riparian land cover	% deciduous/evergreen/mixed forest and grassland in riparian zone	NLCD 2011 (Homer et al. 2015)	0.14
Future/projected water temperature	Temperature (°C)	Carlson et al. 2017b,c	0.11

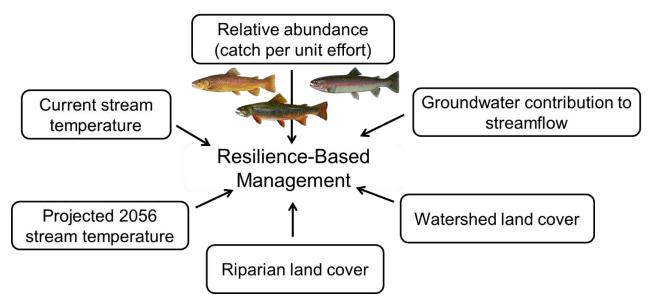


FIGURE 3.2. Conceptual map depicting connections between important thermal drivers in Michigan trout streams (i.e., stream prioritization tool criteria [boxes]) and resilience-based management that promotes thermally resilient streams.

which generally increase temperatures relative to upstream reaches in Michigan streams (Lessard and Hayes 2003) and thus bias water temperature models and associated predictions. Mean July stream temperatures were calculated for each stream because this month, generally the warmest and most thermally stressful for trout in Michigan (Zorn et al. 2011), is likely to be the time period during which trout thermal habitat quality and quantity is first affected by climate change. Mean daily water temperatures in July from the year 2006 were used to define the water temperature criterion for the SPT because records for this year were most spatially extensive and complete.

The predicted change in water temperature resulting from climate change projections for each stream was also used as an SPT criterion (Figure 3.2). Stream temperatures in the year 2056 were projected by integrating future air temperature predictions into air-water temperature regression models. Stream-specific regression models were developed by pairing historical air and water temperatures for each stream. The United States Department of Energy Historical Climate Network (CDIAC 2016) was used to obtain daily July air temperatures measured from 1990 to 2010 for each stream. Air temperatures were collected from the gauging station closest to each stream's headwaters, where MDNR gauges recorded water temperatures. Stream-specific regression models were generated by pairing mean July air and water temperatures from recent years (i.e., 2002–2010) for the 28 streams for which historical stream temperatures were available (Figure 3.1). If streams did not have historical water temperatures, generalized (i.e., region-specific) air-water temperature models were used (Carlson et al. 2017b). In particular, the Stefan and Preud'homme (1993) stream temperature model was developed specifically for surface runoff-dominated streams and estimates weekly stream temperature by:

 $T_w = 0.86T_a + 2.9$,

where T_w is water temperature (°C) and T_a is air temperature (°C). To predict water temperatures in groundwater-dominated streams, the Krider et al. (2013) model estimates weekly stream temperature is estimated by:

 $T_w = 0.38T_a + 6.63$,

where T_w is water temperature (°C) and T_a is air temperature (°C).

After developing air-water temperature models for all 52 streams, future stream temperatures were predicted and incorporated into the SPT as indices of projected changes in water temperature resulting from changes in air temperature. Mean July air temperatures were forecasted in 2056 using three coupled climate models (CCMs) based on the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project phase 3 (CMIP3): the Third Generation Coupled Global Climate Model (CGCM3, Canadian Centre for Climate Modelling and Analysis), the CM2 Global Coupled Climate Model (CM2, Geophysical Fluid Dynamics Laboratory at the National Oceanic and Atmospheric Administration) and the Hadley Centre Coupled Model version 3 (HadCM3, Met Office, United Kingdom's National Weather Service). The bias-correction spatial disaggregation (BCSD) approach was used to spatially downscale each climate model's resolution (~200 X 200 km) to a 12 X 12 km scale suitable for Michigan streams (Maurer et al. 2007). Air temperatures were projected for each stream's subbasin (HUC8) as defined in the National Hydrography Dataset Plus Version 1 (NHDPlusV1).

uncertainty, temperature drivers (e.g., forest canopy density, atmospheric pressure, soil layering), and range of predicted air temperatures unique to each model. Finally, future stream temperatures were predicted by calculating the products of air temperature regression coefficients and CCM air temperature means and adding them to model intercepts (i.e., stream temperature = air temperature coefficient*projected future air temperature + intercept).

Future stream temperature projections were then compared with species-specific temperature thresholds for growth and survival to assign thermal habitat suitability statuses for each stream. We obtained threshold temperatures from United States Fish and Wildlife Service (USFWS) Biological Reports (e.g., Raleigh 1982a, 1982b; Raleigh et al. 1986) containing thermal habitat status temperature ranges for juveniles and adults of each species. Other sources (i.e., Fry et al. 1946; Baldwin 1957; Elliott and Hurley 2000; Hay et al. 2006) contained temperature ranges for juveniles or adults and were used to confirm temperatures reported in the USFWS reports. When threshold temperatures (e.g., thermal minima, maxima) differed between juveniles and adults, we reported juvenile temperatures under the premise that resilient salmonid fisheries can only be conserved if young fish survive to adulthood. We designated status 1 streams as those that had mean July temperatures that were optimal for growth of Brook Trout (11.0–16.5 °C; Raleigh 1982a), Brown Trout (12.0–17.0 °C; Raleigh et al. 1986; Hay et al. 2006), and Rainbow Trout (12.0–16.4 °C; Raleigh 1982b). Temperatures of status 2 streams were suitable, but not optimal, for growth of Brook Trout (16.5-20.5 °C; Raleigh 1982a), Brown Trout (17.0–20.0 °C; Elliott and Hurley 2000), and Rainbow Trout (16.4–22.5 °C; Raleigh 1982b). Status 3 streams were too warm for growth (in July) of Brook Trout ($20.5-25.3 \text{ }^{\circ}\text{C}$; Baldwin 1957; Raleigh 1982a), Brown Trout (20.0–26.2 °C; Hay et al. 2006), and Rainbow Trout (22.5–25.0 °C; Raleigh 1982b). Finally, temperatures of status 4 streams resulted in high

mortality risk for Brook Trout (> 25.3 °C; Fry et al. 1946; Raleigh 1982a), Brown Trout (> 26.2 °C; Hay et al. 2006), and Rainbow Trout (> 25.0 °C; Raleigh 1982b).

Trout population characteristics

The presence/absence and relative abundance of Brook Trout, Brown Trout, and Rainbow Trout (i.e., catch per unit effort [number of fish/mile] from standardized electrofishing surveys) were also used as an input criterion for the SPT (Figure 3.2). These trout population characteristics were obtained for all 52 streams from a MDNR report documenting the status and trends of Michigan stream resources (Wills et al. 2015). Relative abundance was converted to a categorical measurement as defined by the MDNR (Wills et al. 2015): high abundance (>75th percentile; Brook Trout: > 560 fish/mile; Brown Trout: > 548 fish/mile; Rainbow Trout: > 128 fish/mile), medium abundance (25th-75th percentile; Brook Trout: 29-560 fish/mile; Brown Trout: 39-548 fish/mile; Rainbow Trout: 13-128 fish/mile), and low abundance (< 25th percentile; Brook Trout: < 29 fish/mile; Brown Trout: < 39 fish/mile; Rainbow Trout: < 13 fish/mile).

Groundwater contribution to streamflow

Groundwater was used as an input criterion for the SPT (Figure 3.2) because it has been reported to provide temperature buffering and flow stability that often make streams thermally suitable for trout throughout the year (Menberg et al. 2014; Carlson et al. 2017c). Stream-specific groundwater inputs were assessed using baseflow, the proportion of streamflow attributable to groundwater. Baseflow was expressed as baseflow index (BFI), the mean baseflow (mm*year⁻¹) divided by total streamflow (mm*year⁻¹), values of which were obtained

from a United States Geological Survey report (Neff et al. 2005). BFI values range from zero (i.e., no groundwater) to one (i.e., all groundwater; Wahl and Wahl 1988). A digital filter hydrograph separation technique was used to calculate BFI by partitioning daily streamflow records into their groundwater and surface-runoff components. Groundwater-dominated streams were those with BFI > 0.60, whereas surface runoff-dominated systems were those with BFI \leq 0.60 (McKergow et al. 2005; Dukić and Mihailović 2012).

Watershed and riparian land cover

Percentages of each stream's watershed and riparian zone composed of deciduous forest, evergreen forest, mixed forest, or grassland were used as SPT input criteria (Figure 3.2) because these land cover types are typically associated with optimal or near-optimal trout thermal habitats (Siitari et al. 2011; Carlson et al. 2016). Watershed and riparian land cover were evaluated using the National Land Cover Database (NLCD) 2011 (Homer et al. 2015). Riparian zone width was defined as 100 m to be consistent with previous trout stream research (Vondracek et al. 2005; Carlson et al. 2016).

Stream prioritization tool development

The SPT was developed in collaboration with fisheries professionals from MDNR and the United States Geological Survey (USGS) using the Management Unit Prioritization Tool framework (Rohweder et al. 2015a, 2015b). Results from the fisheries professional survey were used to define six SPT criteria important for resilience-based salmonid management (Figure 3.2), along with their weights (Table 3.1). Higher weights corresponded to higher priority, with the sum of weights for all criteria equaling one.

Output scores for each criterion were calculated such that higher scores corresponded with higher-quality thermal habitat conditions for trout as defined by temperature, groundwater input, and watershed/riparian land cover or, for the trout population characteristics criterion, higher-quality trout populations (as defined by species presence and relative abundance). Because higher BFI values corresponded with higher-quality trout thermal habitat conditions, BFI values were not adjusted to calculate scores for the groundwater contribution criterion. However, water temperatures in 2006 and 2056 had to be adjusted so that lower (i.e., more optimal) temperatures produced greater SPT scores, and vice versa. This was achieved by subtracting each temperature from a reference value (i.e., 25 °C) greater than the maximum temperature so that cooler temperatures received higher scores and warmer temperatures received lower scores. Scores for the trout population characteristics criterion were assigned in binary format for presence (score = 1) and absence (score = 0) and increasing numerical format for low relative abundance (score = 1), medium relative abundance (score = 2), and high relative abundance (score = 3; Wills et al. 2015). Scores were summed across species such that streams with Brook Trout, Brown Trout, and Rainbow Trout in high abundance received higher scores than streams with low abundance or absent trout species. Cumulative percentages of each stream's watershed and riparian zone comprised of deciduous forest, evergreen forest, mixed forest, and grassland represented scores for the watershed and riparian land cover criteria, respectively.

For each stream, output scores for each input criterion were normalized to a consistent scale of 0 to 100 using the following formula (Rohweder et al. 2015a, 2015b):

<u>individual – minimum</u> * 100 <u>maximum – minimum</u> * 100

where "individual" denotes individual stream score, "minimum" denotes the minimum score of all streams, and "maximum" denotes the maximum score of all streams. This calculation was performed individually for each input criterion. Normalized scores for each criterion were multiplied by manager-defined weights to produce weighted scores. Then, weighted scores were added to produce a final output score for each stream representing its importance for current and future trout management (i.e., "stream importance"; Figure 3.3). Lastly, streams were ranked by final output scores, which represented each stream's overall importance relative to other streams.

The SPT was designed and delivered to Michigan fisheries professionals (e.g., managers, biologists, policy makers) for use in stream trout management via Data Basin (https://databasin.org), an open-access mapping and analysis platform that allows users to specify input criteria, set constraints, define management area boundaries, and visualize outcomes of potential decisions. Spatial data representing each of the six input criteria were assembled in ArcMap 10.4 (Environmental Systems Research Institute, Redlands, California) and exported to Data Basin for display and dissemination to fisheries professionals. Choosing an open-access platform such as Data Basin, as opposed to a proprietary geographic information systems platform with limited accessibility, was an important prerequisite for delivering the SPT to Michigan fisheries professionals in an accessible, user-friendly manner. Data Basin was configured to display six map layers corresponding to each of the SPT criteria. Each criterion layer was equipped with clearly defined symbols and color codes to depict important difference among streams (e.g., water temperatures, trout population characteristics, watershed land cover). A final map layer was created to display stream importance scores and allow comparisons among streams. SPT users have the ability to enable/disable these seven map layers at their discretion to create map combinations in accordance with their decision-making needs (e.g., evaluating stream

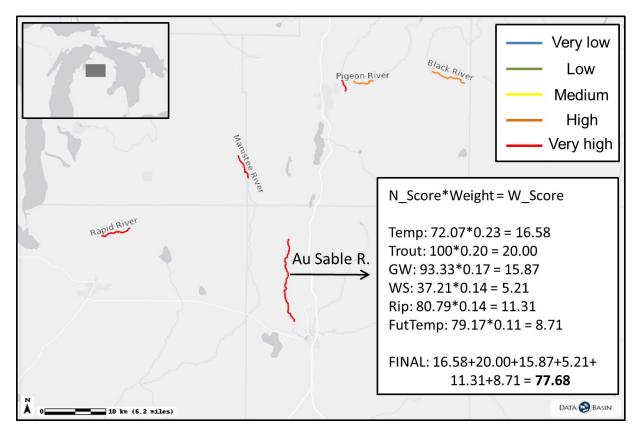


FIGURE 3.3. Example of how normalized output scores (N_score) for each input criterion (Table 1) were multiplied by manager-defined weights to produce weighted scores (W_score). These scores were then added for all criteria to produce a final output score for each stream reflecting its relative importance for trout management in a changing climate.

thermal regimes, assessing stream riparian habitat conditions, deciding which streams warrant habitat rehabilitation). The SPT is available for fisheries professionals and other interested parties at <u>http://bit.ly/2KPPojq</u>.

Results

Stream temperature

Streams which currently have optimal temperatures for trout growth and survival were projected to sustain their high-quality thermal conditions through at least 2056. Davenport Creek (eastern Upper Peninsula; Figure 3.1) had the coolest current July water temperature (11.5°C) and therefore received the highest ranking for the water temperature criterion, making it the most thermally optimal trout stream in the present (Table 3.2). Other highly-ranked streams with respect to water temperature included the West Branch Sturgeon River (13.3°C, northern Lower Peninsula), Manistee River (13.6°C, northern Lower Peninsula), and Carlton Creek (14.0°C, western Lower Peninsula; Figure 3.1). For the projected future water temperature criterion, Davenport Creek and the West Branch Sturgeon and Manistee rivers were again the highestranked streams by the SPT, with predicted mean July water temperatures in the year 2056 that were $\leq 14.2^{\circ}$ C (Table 3.2).

Trout population characteristics

The highest-ranked systems for the trout population characteristics criterion were three of Michigan's currently important streams for trout angling (Table 3.2). High rankings for the Au Sable, Manistee, and West Branch Sturgeon rivers in Michigan's northern Lower Peninsula (Figure 3.1) reflected the fact that all three trout species (i.e., Brook Trout, Brown Trout, TABLE 3.2. Overall stream rankings based on six stream prioritization tool (SPT) criteria. Columns correspond to six SPT criteria: water temperature (Temp); trout population characteristics (Trout); groundwater contribution to stream flow (GW) expressed as baseflow index, the mean baseflow divided by total streamflow; percent watershed (WS) and riparian (Rip) land cover composed of deciduous forest, evergreen forest, mixed forest, and grassland; and projected 2056 water temperature (FutTemp). The Trout column was calculated by adding two scores across species (i.e., Brook Trout, Brown Trout, Rainbow Trout): presence/absence (score = 1/0) and relative abundance (score = 1 [low], 2 [medium], 3 [high]) as defined by Wills et al. (2015). R. denotes river and Crk. denotes creek. NLP, SLP, and UP refer to Michigan's Northern Lower Peninsula, Southern Lower Peninsula, and Upper Peninsula.

Stream	Overall	Temp	Trout	GW	WS	Rip	FutTemp
Au Sable R.	1	14.5 (9)	12(1)	0.72 (6)	35.8 (25)	76.4 (10)	14.9 (9)
Bark R.	47	19.9 (45)	2 (41)	0.60 (27)	32.0 (30)	31.3 (39)	21.2 (43)
Bear Crk.	32	15.8 (28)	4 (17)	0.65 (8)	23.3 (36)	9.4 (49)	18.2 (31)
Black R.	27	15.1 (21)	4 (17)	0.55 (35)	7.0 (48)	68.3 (17)	16 (20)
Boardman R.	10	15.0 (20)	8 (6)	0.63 (17)	39.2 (20)	60.1 (20)	15.5 (18)
Brule R.	45	19.7 (42)	3 (34)	0.52 (38)	32.1 (29)	58.5 (21)	21.1 (40)
Bryan Crk.	25	16.7 (33)	2 (41)	0.60 (27)	58.4 (10)	89.2 (3)	19.4 (36)
Canada Crk.	49	20.0 (47)	2 (41)	0.55 (35)	16.5 (40)	55.8 (23)	21.9 (47)
Carlton Crk.	16	14.0 (4)	3 (34)	0.73 (3)	17.8 (39)	35.1 (37)	14.6 (4)
Carp R.	30	17.6 (35)	8 (6)	0.60 (27)	20.5 (37)	23.8 (44)	19.0 (32)
Cedar Crk.	44	18.3 (37)	7 (8)	0.50 (44)	8.4 (47)	21.0 (45)	20.1 (37)
Cedar R. (SLP)	48	16.3 (31)	3 (34)	0.60 (27)	39.8 (19)	46.3 (30)	23.2 (49)
Cedar R. (UP)	37	21.8 (51)	2 (41)	0.60 (27)	12.5 (43)	42.9 (31)	16.9 (27)
Chocolay R.	14	15.2 (22)	4 (17)	0.56 (34)	54.0 (12)	80.1 (8)	16.3 (24)
Coldwater R.	52	22.6 (52)	4 (17)	0.45 (49)	18.2 (38)	5.8 (51)	24.4 (52)
Davenport Crk.	8	11.5 (1)	3 (34)	0.57 (32)	96.3 (1)	41.6 (34)	12.4 (1)
Duke Crk.	43	15.3 (23)	4 (17)	0.50 (44)	11.0 (45)	11.64 (48)	19.1 (33)
E. Branch Fox R.	3	14.2 (7)	6 (11)	0.73 (3)	79.6 (5)	93.9 (1)	15.3 (12)
Elm R.	35	17.5 (34)	4 (17)	0.45 (49)	66.8 (7)	89.89 (2)	24.3 (51)
Escanaba R.	46	20.0 (47)	5 (14)	0.44 (52)	49.0 (13)	36.4 (35)	20.5 (38)
Falls R.	33	19.9 (45)	4 (17)	0.52 (38)	83.4 (4)	67.7 (18)	21.4 (45)

TABLE 3.2 (cont'd).

Stream	Overall	Temp	Trout	GW	WS	Rip	FutTemp
Hersey R.	18	14.7 (14)	4 (17)	0.62 (20)	38.3 (22)	46.9 (28)	15.3 (12)
Iron R.	42	18.6 (41)	2 (41)	0.52 (38)	30.6 (32)	57.2 (22)	19.2 (34)
Little Indian R.	11	16.2 (30)	3 (34)	0.73 (3)	62.7 (9)	82.2 (7)	16.4 (25)
Little Muskegon R.	24	14.7 (14)	4 (17)	0.62 (20)	28.3 (33)	33.4 (38)	15.3 (12)
Manistee R.	5	13.6 (3)	12 (1)	0.65 (8)	2.9 (50)	68.5 (16)	14.2 (3)
Mann Crk.	7	15.4 (24)	4 (17)	0.65 (8)	84.0 (3)	88.6 (4)	16.2 (21)
Martin Crk.	20	14.9 (19)	4 (17)	0.61 (25)	24.7 (35)	54.8 (24)	15.5 (18)
Menominee R.	50	20.5 (50)	2 (41)	0.57 (32)	37.2 (23)	25.4 (43)	21.7 (46)
Miller Crk.	19	15.4 (24)	2 (41)	0.65 (8)	56.2 (11)	50.3 (27)	16.2 (21)
Mosquito Crk.	29	14.7 (14)	2 (41)	0.62 (20)	32.2 (28)	30.4 (40)	15.3 (12)
Muskegon R.	31	14.7 (14)	4 (17)	0.62 (20)	14.9 (42)	9.2 (50)	15.3 (12)
Ogontz R.	15	14.1 (5)	2 (41)	0.74 (1)	38.8 (21)	28.0 (41)	14.7 (6)
Paint R.	41	19.7 (42)	3 (34)	0.52 (38)	32.7 (26)	70.2 (14)	21.1 (40)
Pere Marquette R.	22	16.6 (32)	4 (17)	0.61 (25)	40.2 (18)	69.3 (15)	17.4 (30)
Pigeon R.	12	14.5 (9)	7 (8)	0.65 (8)	6.5 (49)	53.0 (26)	14.6 (4)
Pine R. (NLP)	17	16.0 (29)	11 (4)	0.65 (8)	32.3 (27)	27.8 (42)	16.9 (39)
Pine R. (SLP)	38	18.4 (38)	3 (34)	0.49 (48)	30.8 (31)	41.7 (33)	20.7 (27)
Prairie Crk.	51	18.4 (38)	2 (41)	0.50 (44)	0.0 (51)	2.5 (52)	22 (48)
Rapid R.	4	14.5 (9)	11 (4)	0.63 (17)	26.5 (34)	86.3 (5)	14.9 (9)
Rogue R.	36	18.4 (38)	7 (8)	0.50 (44)	43.0 (16)	35.5 (36)	19.2 (34)
S. Branch Pine R.	21	14.6 (12)	4 (17)	0.45 (49)	95.1 (2)	53.2 (12)	17.3 (29)
Salmon Trout R.	23	14.6 (12)	2 (41)	0.65 (8)	48.5 (14)	46.6 (25)	16.2 (21)
Silver Crk.	9	15.4 (24)	4 (17)	0.72 (6)	36.9 (24)	75.2 (29)	14.9 (9)
St. Joseph R.	28	15.6 (27)	6 (11)	0.63 (17)	11.6 (44)	13.1 (47)	16.4 (25)
Sturgeon R.	6	14.1 (5)	6 (11)	0.74 (1)	42.9 (17)	74.0 (13)	14.7 (6)
Tahquamenon R.	39	20.0 (47)	2 (41)	0.55 (35)	65.1 (8)	78.9 (9)	23.6 (50)
Tamarack Crk.	26	14.7 (14)	5 (14)	0.62 (20)	16.1 (41)	19.0 (46)	15.3 (12)

TABLE 3.2 (cont'd).

Stream	Overall	Temp	Trout	GW	WS	Rip	FutTemp
W. Branch Maple R.	13	14.4 (8)	4 (17)	0.65 (8)	0.0 (51)	83.3 (6)	14.8 (8)
W. Branch Sturgeon R.	2	13.3 (2)	12(1)	0.65 (8)	69.3 (6)	42.6 (32)	13.4 (2)
Yellow Dog R.	34	18.0 (36)	4 (17)	0.52 (38)	47.1 (15)	75.4 (11)	21.3 (44)

Rainbow Trout) were abundant in these systems. The Pine River (southern Lower Peninsula) and Rapid River (northern Lower Peninsula) were both ranked fourth, and the Boardman River (northern Lower Peninsula) and Carp River (eastern Upper Peninsula) were ranked sixth with respect to trout population characteristics (Table 3.2, Figure 3.1). As such, the three trout species were relatively abundant in these streams compared to the 45 lower-ranked systems, likely due to the presence of thermally favorable conditions (e.g., groundwater, watershed/riparian land cover).

Groundwater contribution

Groundwater inputs are important for trout thermal habitat quality because they buffer against temperature extremes in the summer and winter. With a comparatively high BFI of 0.74, the Ogontz and Sturgeon rivers (central Upper Peninsula) were the highest-ranked streams by the SPT in terms of groundwater contribution to streamflow (Table 3.2, Figure 3.1). Five other trout streams (i.e., East Branch Fox and Little Indian rivers, central Upper Peninsula; Au Sable and South Branch Pine rivers, northern Lower Peninsula; Carlton Creek; Figure 3.1) ranked among the top seven systems had BFI values > 0.70, meaning they are thermally buffered by groundwater input and thus likely to maintain optimal or suitable thermal habitat conditions for Brook Trout, Brown Trout, and Rainbow Trout in a warming climate.

Watershed and riparian land cover

Streams with the greatest proportion of watershed land cover types that promote highquality trout thermal habitats (i.e., deciduous forest, evergreen forest, mixed forest, grassland) included Davenport Creek (96.3%) and the South Branch Pine River (95.1%), both of which are located in relatively rural, undeveloped parts of Michigan (i.e., eastern Upper Peninsula, northeastern Lower Peninsula; Table 3.2, Figure 3.1). Other highly-ranked streams for the watershed land cover criterion included Mann Creek (southern Lower Peninsula), the Falls River (western Upper Peninsula, Figure 3.1), and the East Branch Fox River, each with 79.6–84.0% of their watersheds composed of land cover types associated with high-quality stream thermal habitats. Similar to watershed land cover, the highest-ranked stream for the riparian land cover criterion (i.e., East Branch Fox River; Table 3.2, Figure 3.4) was a rural, undeveloped central Upper Peninsula system with 93.9% of its riparian zone containing thermally favorable trout habitat types. The Elm River (western Upper Peninsula), Bryan Creek (central Upper Peninsula), and Mann Creek were also highly-ranked streams with 88.6–89.9% of their riparian zones comprised of thermally favorable habitat types.

Considering all six criteria simultaneously, the highest-ranked streams by the SPT (i.e., greatest importance for current and future trout management) were the Au Sable, West Branch Sturgeon, East Branch Fox, Rapid, and Manistee rivers (Table 3.2, Figure 3.5).

Discussion

Uncertainty is ubiquitous in the decision-making processes of fisheries management as fisheries are ecologically and socioeconomically complex systems, yet decisions must be made continually to sustain fish communities and the human systems they support. Previous studies in the fledgling field of fisheries decision support have focused primarily on marine fisheries, particularly how DSTs can help fisheries professionals balance economic and ecological objectives in fisheries management decision-making. For instance, Dichmont et al. (2013) used a DST to develop MPA closure strategies that balanced economic and ecological objectives for

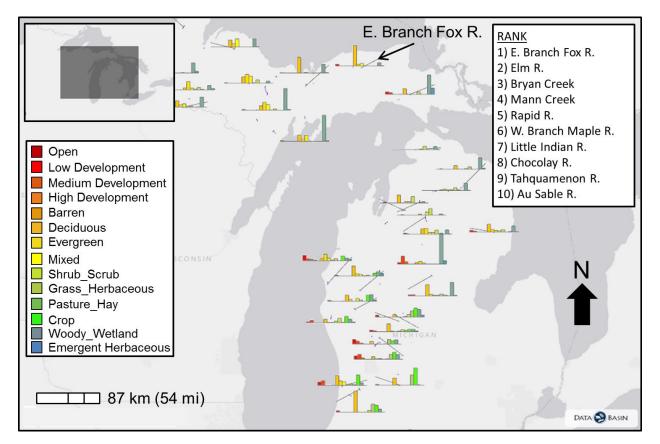


FIGURE 3.4. Michigan stream rankings for a stream prioritization tool criterion about highquality riparian land cover conditions. Streams were ranked according to the proportion of their riparian zones containing habitats that promote cool, thermally favorable conditions for trout (i.e., deciduous/evergreen/mixed forest, grassland), with higher rankings indicating greater coverage by thermally favorable habitats. The ten highest-ranked streams by the SPT with respect to riparian land cover conditions are included above.

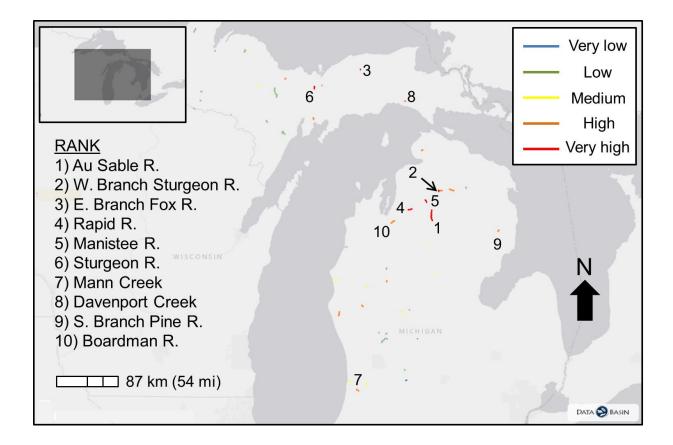


FIGURE 3.5. Overall Michigan stream importance rankings considering all six stream prioritization tool (SPT) criteria (i.e., water temperature, trout relative abundance, groundwater contribution to stream flow, high-quality watershed land cover, high-quality riparian land cover, projected 2056 water temperature). Streams with greater scores for individual criteria received higher importance rankings. The ten highest-ranked streams with respect to all six SPT criteria are included above.

marine fisheries, similar to how Azadivar et al. (2009) and Stortini et al. (2015) used DSTs to identify management approaches that minimized mortality of marine fishes while maximizing socioeconomic benefits (e.g., food, revenue, employment). Despite the scarcity of DSTs in freshwater fisheries, the present study helps fill this knowledge gap by illustrating how collaboration among freshwater fisheries scientists, managers, biologists, and policy makers generated an SPT that integrates diverse information for robust decision-making regarding stream trout thermal habitat management.

By providing information on stream-specific thermal habitat conditions (e.g., current/future temperature, groundwater input, riparian habitat), the SPT enables fisheries professionals to select streams and time periods for which resource allocation (e.g., money, personnel, equipment) will most efficiently and effectively promote resilience-based management objectives. In the present study, some of the SPT rankings supported extant knowledge of Michigan trout streams, whereas others were unexpected and enhanced understanding of these systems. For instance, the Au Sable River was the highest-ranked stream with respect to all SPT criteria collectively (Figure 3.2), which confirms the river's status as a renowned highly regarded trout fishery, a National Wild and Scenic River, and a Michigan Blue Ribbon Trout Stream (Zorn and Sendek 2001; Canale and Chapra 2016). Similarly, the Manistee River's fifth-highest ranking substantiated the fact that this stream currently supports a productive, highly valued trout fishery (Tyler and Rutherford 2007; Danhoff et al. 2017). Sixty percent of the ten highest-ranked trout streams were located in the Northern Lower Peninsula (NLP) of Michigan, where geological, climatic, hydrological, and thermal conditions are known to provide cold, well-oxygenated streams for productive trout fisheries (T. Zorn, MDNR, personal communication). However, certain socioeconomically important systems currently

valuable for angling (e.g., Muskegon River, Pere Marquette River) were projected to have relatively poor thermal habitat quality in a changing climate. Moreover, streams without top-tier fisheries (e.g., Rapid River, Davenport Creek) were predicted to have excellent habitat quality for the trout populations studied. These results indicate that the Rapid River, Davenport Creek, and other highly-ranked, lesser-known systems merit management efforts to maintain and enhance trout populations and their thermal habitats. In addition, these findings illustrate how the SPT revealed surprising, management-relevant findings and represents a flexible instrument for fisheries professionals as they make decisions for resilience-based salmonid management in a changing climate.

An important consideration in designing the SPT was the primacy of *providing* fisheries professionals with integrative information (e.g., stream temperatures, groundwater, land cover, trout population characteristics), rather than *prescribing* decisions for them. After all, stream-specific ecological and socioeconomic circumstances will ultimately dictate how fisheries professionals use the information the SPT supplies, in accordance with the eight steps of the fisheries management process (Taylor et al. 1995). For instance, high-importance streams (as ranked herein) may be high-priority when socio-political circumstances favor trophy fisheries management, threatened/endangered species conservation, or other outcomes that require active, on-the-ground management approaches. However, high-importance streams according to our rankings may be low-priority when managers deem it most important to rehabilitate lower-ranked systems that are unlikely to sustain themselves without management intervention. The intention of co-producing an SPT with fisheries professionals was to ensure that they received the information they deemed most important via an integrative tool to inform – not execute – decision-making. By supporting, rather than making, stream fisheries management decisions, the

SPT is an adaptable instrument for balancing ecological and socioeconomic objectives given changes in the environment and human systems over time. The SPT was also timely as it was concurrent with development of statewide inland trout management plan by the MDNR (Carlson and Zorn 2018; Zorn et al. 2018). At a time when ecological and social data on trout fisheries are being assimilated and important policy and management decisions are imminent, it is advantageous for Michigan fisheries professionals to have an SPT to assist them in synthesizing multiple management priorities for efficient, effective decision-making.

As a mechanism for enhancing trout management in a changing climate, the SPT described in this study enables fisheries professionals to forecast future thermal habitat conditions and proactively manage trout populations, thereby promoting a resilience approach to stream trout management. Resilience-based fisheries management recognizes the importance of maintaining or restoring the capacity of habitats, populations, communities, and ecosystems to resist and recover from environmental disturbances, including those associated with a changing climate (Waldman et al. 2016; Carlson et al. 2017c). Today, warming air and water temperatures are impacting fisheries from the individual to ecosystem levels (Paukert et al. 2016) and affecting fisheries stakeholders' opportunities (e.g., commercial, recreational, subsistence) and livelihoods via changes in fish abundance and distribution (Hunt et al. 2016). Given that the natural and human components of fisheries systems are changing as the climate warms, it is important to manage fisheries for resilience. Because fisheries affect – and are affected by – extant biological, social, economic, and political conditions, resilience-based management requires collaboration among diverse fisheries and land management professionals and stakeholders and consideration of ecological and socioeconomic information to facilitate robust, integrated management strategies (Carlson et al. 2017c). As illustrated herein, the SPT is an

instrument for the development and assessment of resilience-based salmonid management programs because it arose from science-management collaboration and integrates information about the structure and function of fisheries ecosystems and their interactions with human systems, thereby facilitating social-ecological resilience.

Through a case study involving coldwater stream trout management, this investigation advances previous research on fisheries decision support by demonstrating the utility of an SPT for Michigan trout management in a changing climate. The SPT developed herein enables fisheries professionals to predict the effects of climate change in Michigan trout streams (e.g., magnitude and spatiotemporal distribution of warming), evaluate the need for and appropriateness of fisheries management actions (e.g., thermal habitat management, fish stocking), and prioritize future habitat management and rehabilitation activities in multiple watersheds. Despite the value of the SPT (and, more broadly, DSTs) for informing fisheries management, decision support is an emerging subdiscipline in the fisheries profession and thus requires further research to broaden and deepen its contribution to fisheries resilience and sustainability. For instance, most fisheries DSTs (Azadivar et al. 2009; Dichmont et al. 2013; Stortini et al. 2015; Bitunjac et al. 2016) have been applied to inform decision-making in marine commercial systems rather than freshwater or recreational fisheries (but see Canale and Chapra 2016). Hence, there is a pressing need to develop DSTs applicable to freshwater fisheries in both commercial and recreational contexts and usable by diverse stakeholder groups (e.g., state and federal fisheries management agencies, non-governmental organizations, anglers, general public) to enhance fisheries sustainability.

Research at broader spatial and longer temporal scales is necessary to advance the science and practice of freshwater fisheries decision support. Although we focused our research

intensively on Michigan's coldwater streams given their hydrological and thermal diversity and socioeconomic value, we conducted this study with the understanding that our approach for SPT development and implementation could be readily applied to other fisheries outside Michigan. Indeed, there are numerous opportunities for fisheries professionals to apply our methods to enhance the efficiency and effectiveness of fisheries management for different species and ecosystems (e.g., lakes, rivers, wetlands). Climate change adaptation formed the conceptual underpinning for the present study, but climate change is certainly not the only stressor affecting fisheries worldwide. There is a need for DSTs that inform fisheries decision-making amid additional ecosystems threats (e.g., invasive species, hydropower expansion), the development of which will require co-production among scientists, managers, biologists, policy makers, and other fisheries stakeholders. Finally, continuing to engage the public in the process of DST development will make fisheries conservation a more collaborative, socially acceptable endeavor (Irvin and Stansbury 2004; Azadivar et al. 2009; NRC 2010; Carlson et al. 2017c) that promotes resilience-based fisheries management and enhances the value and sustainability of the world's fisheries resources.

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Rubenstein, L. Thompson, J. Thornley, S. Weiskopf) for their warm collegiality as the first author spent time in residence at headquarters in Reston, Virginia. We acknowledge other USGS professionals (K. Jenni, C. Thatcher) for their helpful insights regarding development of the stream prioritization tool (SPT) described herein. APPENDIX

Appendix 3.1. Survey instrument sent to Michigan fisheries professionals.

MICHIGAN TROUT STREAM MANAGEMENT IN A CHANGING CLIMATE A Survey of Michigan Fisheries Professionals

You are being asked to take part in a research study on stream trout management in Michigan given the potential for a changing climate regime. The survey is designed to evaluate the opinions and perspectives of Michigan Department of Natural Resources (MDNR) fisheries professionals regarding management of inland stream trout (i.e., brook trout, brown trout, rainbow trout) in Michigan given the threat of a warming climate.

Results from this survey will be combined with results from ongoing stream temperature modeling performed by the survey authors to project the effects of a changing climate regime on growth and survival of brook trout, brown trout, and rainbow trout in Michigan. Survey results will also be integrated with those from the 2015 MDNR Michigan Inland Trout Angler Survey. The ultimate goal of this project is to design a user-friendly, map-based **decision-support tool** in collaboration with the United States Geological Survey that assists Michigan fisheries professionals in planning trout stream management programs that promote thermally resilient streams and productive stream trout populations. *Decision-support tools aid decision making by systematically incorporating information, accounting for uncertainties, and facilitating evaluation of tradeoffs between alternatives*. In the 2013-2017 MDNR Fisheries Division Strategic Plan, Goal Four (Objective Two) expresses the need for decision-support tools and describes their value for optimizing management of Michigan's fisheries and aquatic resources.

By completing this survey, you are contributing to an important task of enhancing coldwater trout stream management amidst a changing climate regime. If you choose to participate, you will fill out **a voluntary, anonymous survey** on your perceptions of current and future trout stream management, including the potential use of decision-support tools for management decision-making. Your answers will be confidential. Your participation in the project is completely anonymous, voluntary, and uncompensated. Your participation **will assist with the development of a useful decision-support tool to inform stream trout management in a changing climate**. *There is no penalty or loss of benefits if you chose not to participate. You can skip any questions or withdraw at any time*.

If you have any questions about the research study, please contact Andrew Carlson (carls422@msu.edu) or Bill Taylor (taylorw@msu.edu). If you have any questions or concerns about your role and rights as a research participant, would like to obtain information or offer input, or would like to register a complaint about this research study, you may contact, anonymously if you wish, the Michigan State University Human Research Protection Program at PHONE: 517-355-2180, FAX: 517-432-4503, EMAIL: irb@msu.edu, or MAIL: 207 Olds Hall, MSU, East Lansing, MI 48824. *Please ask any questions you may have before agreeing to participate in this study. Thank you for your contribution to this important study.*

STATEMENT OF CONSENT: I have read the above information and have received answers to any questions I asked. I consent to take part in this study.

Your Signature	Date
Your Name (printed) _	

MICHIGAN TROUT STREAM MANAGEMENT IN A CHANGING CLIMATE A Survey of Michigan Fisheries Professionals

Please complete the survey by checking the appropriate box or filling in the blank. Thank you for your time and effort in completing the survey.

Sincerely,

Andrew Carlson Ph.D. Student Michigan State University

Please list your agency name. _____

Please check the Michigan peninsula and region you work in (Upper, Northern Lower, Southern Lower).

Upper Northern Lower Southern Lower

Please list the Michigan fisheries management unit you work in (Western Lake Superior, Eastern Lake Superior, Northern Lake Michigan, Northern Lake Huron, Central Lake Michigan, Southern Lake Huron, Southern Lake Michigan, Lake Erie).

Please list the MDNR office/station/service center (hereafter "office") you work in (e.g., Escanaba, Cadillac, Traverse City, Harrietta)

PART A. Stream trout management

A1. Does your office manage <u>stream trout</u> fisheries (i.e., brook trout, brown trout, or rainbow trout)? _____Yes (go A2) _____No (skip to Part B)

A2. How important do you think the following criteria for prioritizing streams for trout management in your region? Please <u>specify other criteria</u> if they are not listed here.

Criteria	Very important	Important	Somewhat Important	Unimportant	Not sure
Abundance of brook trout					
Abundance of brown trout					
Abundance of rainbow trout					
Angler use					
Proximity to office					
In-stream habitat quality					
Riparian habitat quality					
Groundwater input					
Stream is currently thermally optimal for trout					
Other:					

A3. Based on the criteria you specified in question A2, please list the five *trout streams* counties that you think are <u>most important</u> to manage in your district? Please include the name of the county in which each stream is located.

1)	 	 	
5)			

Personnel resources

A4. How many employees in your office are responsible for managing <u>stream</u> fisheries resources (all fish species included, not just trout)?

A5. Of these fisheries employees, how many manage <u>stream trout</u> fisheries as a <u>full-time</u> or <u>part-time</u> job responsibility?

	Full-time
	Part-time
A6. Do limitations in personnel resources affect your office's stream tr	out management
activities?	Yes
	No
A7. If you answered "Yes" to question A6, please briefly explain or list	how personnel
limitations affect stream trout management.	

Financial resources

A8. Approximately what <u>percent</u> of your office's budget is expended on stream trout management?

_____%

A9. Of this budget (stream trout budget), estimate the percent that your office expends for the following activities.

							don t
		0-5%	6-10%	11-25%	26-50%	>50%	know
a)	Management (survey stream fish populations, implement management plans, maintain						
b)	property, etc.) Research (agency stream studies, university- funded studies, NGO-funded studies, etc.)						
c)	Program services (financial management, personnel management, data processing, etc.)						
d)	Education (publications, exhibits, sport shows, talks, media programs, etc.)						
e)	Hatcheries (fish production and stocking, etc.)						
f)	Land acquisition (stream access areas for the public, including parking and ramps, etc.)						
g)	Physical habitat improvement (in-stream structures, riparian planting, etc.)						
h)	Consultative services (cooperative efforts with other agencies, NGOs, public, etc.)						

A10. Do limitations in financial resources affect your office's stream trout management activities? _____Yes ____No

A11. If you answered "Yes" to question A10, please <u>briefly explain or list</u> how financial limitations affect stream trout management.

Time

A12. Approximately what percent of your office's work time is allocated to <u>stream trout</u> <u>fisheries</u> for: Sum to 100%

a)	Management (surveys, plans, maintenance, etc.)	%
b)	Research (with agency, universities, NGOs, etc.)	%
i)	Program services (financial management,	
	personnel management, data processing, etc.)	%
c)	Education (publications, exhibits, talks, etc.)	%
d)	Hatcheries (fish production and stocking, etc.)	%
e)	Land acquisition (stream access areas for the public)	%
f)	Habitat improvement (in-stream structures, riparian planting, etc.)	%
	-	

Total 100%

A13. Do time limitations affect your office's stream trout management activities? _____Yes ____No A14. If you answered "Yes" to question A13, please <u>briefly explain or list</u> how time limitations affect stream trout management.

A15. Do limitations in equipment/facilities (e.g., vehicles, stream sampling gear, hatcheries) affect your office's stream trout management activities?

Yes ______Yes _____No A16. If you answered "Yes" to question A15, please <u>briefly explain or list</u> how limitations in equipment/facilities affect stream trout management.

PART B. Stream temperature monitoring

B1. Does your office monitor trout stream temperatures? _____Yes ____No

B2. If you answered "Yes" to question **B1**, how often does office monitor trout stream temperatures?

____Seasonally ____Monthly ____Weekly ____Daily ____Hourly

There are two broad approaches that fisheries professionals generally use to describe the relationship between air temperature and stream temperature: *stream-specific* models and *generalized* models. Stream-specific temperature models account for the unique factors that influence each stream's thermal regime (e.g., air temperature, discharge, groundwater input), whereas generalized models are region-specific in representing the thermal regimes of all streams in a particular region. Stream-specific models are generally more accurate in predicting exact temperatures for individual streams as compared to generalized models, but generalized models are more efficient as they require fewer resources (e.g., money, time, personnel) to develop.

B3. Does your office use stream-specific models, generalized models, both, or neither?

Stream-specific models
 Generalized models
 Both
 Neither

B4. Given your office's resource limitations and objectives for stream trout management and stream temperature monitoring/modeling, which model types do you think would be *most useful* for your office (even if you don't currently use them)?

- _____ Stream-specific models (always)
- ____ Generalized models (always)
- _____ Stream-specific models (in certain situations)

Generalized models (in certain situations)
 Models are equally useful
 Models are not useful or my office doesn't monitor stream temperature (If so, why aren't models useful?)

B5. If for question B4 you selected "stream-specific models (in certain situations)" or "generalized models (in certain situations)", please <u>briefly describe</u> those situations.

PART C. Stream thermal habitat management

C1. Does your office manage stream thermal habitats (via groundwater conservation, riparian or watershed protection/rehabilitation, etc.), including collaborative management with other organizations?

Yes (go to C2) No (skip to Part D)

C2. What thermal habitat management strategies for stream trout does your office currently use or plan to use in the future?

Strategy	Current	Future
Groundwater conservation		
Riparian habitat protection		
Riparian habitat rehabilitation		
Watershed habitat protection		
Watershed habitat rehabilitation		
Other:		

C3. Imagine that your office is developing a stream thermal habitat management program. How important do you believe each of the following factors would be? Include a number for each factor indicating its RELATIVE PRIORITY, where larger numbers indicate higher priority. The SUM of numbers for the eight factors should be 100.

		Sum to 100
a)	Current water temperature	
b)	Future/projected water temperature	
c)	Current groundwater contribution	
d)	Future/projected groundwater contribution	
e)	Current surface water contribution	
f)	Future/projected surface water contribution	
g)	Trout population characteristics (presence/absence, relative abundance,	
-	size structure, recreational importance, etc.)	
h)	Riparian attributes (e.g., species composition, shading)	
i)	Watershed land cover (e.g., grassland, forest, agricultural)	
j)	Presence/absence of temperature gauges	
k)	Resource availability (e.g., personnel, finances, time, equipment/facilities))

Total = 100

PART D. Decision-support tools

Results from this survey will be used to develop a decision-support tool to assist Michigan fisheries professionals in planning management programs that promote thermally resilient streams and trout populations. Decision-support tools (DSTs) enable people and organizations to identify policy and management options for achieving their objectives amidst uncertainty. For example, fisheries managers could use a DST to prioritize streams for trout population and thermal habitat management in a changing climate. Imagine a DST for *stream trout management in a changing climate*. This DST combines data on stream temperature and trout populations with information on agency resource availability and trout anglers (e.g., values, opinions, demographics).

D1. How useful do you believe the DST described above would be for stream trout management?

Not usef	ul	Not very useful	Moderately useful	Useful	Very useful	Don't know/no opinion

D2. How can this DST be made as user-friendly as possible? Please <u>specify other features if</u> they are not listed here. (Check all that apply with "X")

Color coding
Symbol coding
Maps included
Delivered via the Internet
Delivered via a GIS program
Written case studies for streams
Background information on DSTs
Other:

Please share additional comments you have about this survey related to trout stream management or decision-support tools in Michigan.

Thank you for participating!

Please return this survey by email to:

Andrew Carlson Michigan State University Email: carls422@msu.edu Phone: 651-280-7013 LITERATURE CITED

LITERATURE CITED

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CHAPTER 4: DEVELOPING PRECIPITATION- AND GROUNDWATER-CORRECTED STREAM TEMPERATURE MODELS TO IMPROVE TROUT MANAGEMENT IN A CHANGING CLIMATE

Carlson, A. K., W. W. Taylor, D. M. Infante. *In review*. Developing precipitation- and groundwater-corrected stream temperature models to improve management of brook charr amid climate change.

The content of this chapter is based on the manuscript cited above, which is currently in review in *Hydrobiologia*. The chapter reflects specifications (e.g., formatting) of this journal and includes additional results and conclusion related to brown trout and rainbow trout.

Abstract

Ensuring the ecological integrity of coldwater streams in a warming world requires understanding how water temperatures changes will affect the sustainability of coldwater fish populations such as brook trout (Salvelinus fontinalis), brown trout (Salmo trutta), and rainbow trout (Oncorhynchus mykiss). However, current models for predicting stream temperature have common flaws, such as assuming spatially uniform (inaccurate) air-stream temperature relationships or requiring measurement of expensive hydrometeorological drivers (e.g., solar radiation, convection) in a manner impractical for fisheries management. Hence, we developed an accurate, cost-effective, management-relevant approach for modeling effects of changes in air temperature, precipitation, and groundwater inputs on coldwater stream temperatures and trout survival and growth in Michigan, USA. Precipitation- and groundwater-corrected regressions were more accurate than air-stream temperature models for predicting stream temperatures. Projected stream warming intensified in proportion to simulated air temperature warming and was most extreme in surface runoff-dominated streams, given their limited groundwater-driven thermal buffering. However, groundwater-dominated streams will not invariably provide coldwater habitats needed by trout if groundwater temperatures increase or groundwater inputs decline due to reduced precipitation. Amid resource limitations, fisheries managers can use our stream temperature modeling approach to predict effects of climate change on trout survival and growth and take actions to facilitate their sustainability in riverine systems.

KEYWORDS: brook trout; brown trout; climate change; groundwater; growth; precipitation; survival; rainbow trout

Introduction

Streams provide important ecological goods and services to humanity (e.g., recreation; water for municipal, industrial, and agricultural use; Loomis et al., 2000), but they are highly vulnerable to certain stressors, including climate change (Woodward et al., 2010) and associated threats to fishes and their habitats (Hershkovitz et al., 2015; Kanno et al., 2015). Climate change has been projected to impact streams through numerous mechanisms, including increased water temperatures (including groundwater) and alterations to hydrological regimes (e.g., more frequent heavy precipitation, reduced snowpack), resulting in changes in thermal and physical habitat for aquatic organisms (Woodward et al., 2010; Snyder et al., 2015). Stream temperature is a fundamental factor influencing the suitability and productivity of stream habitats for aquatic biota. Hence, projected increases in stream temperatures resulting from short- and long-term changes in climate (Thomas et al., 2015; Carlson et al., 2016) are cause for concern among fisheries professionals, policy makers, and allied stakeholders (e.g., non-governmental organizations, general public), particularly those charged with conserving coldwater fishes.

Stream fishes in the family Salmonidae (e.g., brook trout *Salvelinus fontinalis*, brown trout *Salmo trutta*, rainbow trout *Oncorhynchus mykiss*) are adapted to coldwater and coolwater environments and have relatively low thermal tolerance thresholds (Raleigh 1982a,b; Raleigh et al. 1986), making them sensitive to induced stream temperature warming. In addition, stream trout are valuable from ecological, economic, recreational, cultural perspectives (Godby et al. 2007; Tyler & Rutherford 2007). Hence, projecting the effects of climate change on stream trout population viability and productivity is necessary for developing management strategies that will conserve these species in a warming world.

Historically, regression models for predicting stream temperature have included air temperature as a primary driver of water temperature because it is surrogate for solar radiation, the factor that most strongly influences stream temperature (Webb et al., 2008). Despite the importance of understanding how projected changes in air temperature affect stream temperature (i.e., thermal sensitivity), these simple air-stream temperature models ignore other drivers – including groundwater input, precipitation dynamics (e.g., magnitude, intensity), watershed land cover, and riparian shading (Constantz, 1998; Ebersole et al. 2003) – that have the potential to significantly affect stream thermal regimes. Until recently, stream temperature models have largely ignored variability in groundwater dynamics (e.g., magnitude, temperature) among streams and stream reaches, thereby decreasing accuracy of thermal forecasting and efficacy of thermal habitat management in a changing climate, particularly in headwater areas where groundwater inputs tend to be relatively large (Snyder et al., 2015). By accounting for streamand reach-level heterogeneity in groundwater dynamics, groundwater-corrected stream temperature models should provide a more realistic, reliable method for evaluating stream temperature warming than simple air-stream temperature models. Ultimately, this should allow groundwater-corrected stream temperature models to inform thermal habitat management actions needed to facilitate trout population sustainability (e.g., forest canopy rehabilitation, riparian protection).

As a buffer to daily and seasonal temperature alterations, groundwater generally causes stream temperature to be cooler in summer and warmer in winter than streams dominated by surface runoff, particularly in headwater reaches (Webb et al., 2008). Thermal buffering is ecologically important because it may mitigate effects of climate change on coldwater fishes and their habitats. Despite the ecological significance of groundwater, its incorporation into stream

temperature models can be confounded by the complexity of groundwater dynamics, especially heterogeneity in groundwater temperatures and input magnitudes among stream reaches (Snyder et al., 2015). Although stream heat budget models incorporate groundwater and other atmospheric, meteorological, and hydrological variables to predict water temperature (Leach & Moore, 2011; Westhoff et al., 2011), they are expensive, data-intensive, and generally impractical for use in fisheries management (Dunham et al., 2005; Snyder et al., 2015). Groundwater-corrected stream temperature regressions were recently developed to inform brook trout management in the Eastern United States of America (USA; Snyder et al., 2015), but these models did not include other important thermal drivers (e.g., precipitation), nor was their applicability evaluated in other areas that have socio-ecologically valuable populations of brook trout, brown trout, rainbow trout, and other coldwater fishes (e.g., Midwestern USA). Developing a methodology to integrate groundwater and precipitation dynamics into stream temperature modeling is important because it can promote stream management for thermal resilience using readily measureable temperature drivers. More broadly, this endeavor would support resilience-based management programs for coldwater streams that enhance the ability of these ecosystems and associated human systems to absorb disturbances (e.g., temperature changes) and yet retain their overall structure and function (Carlson et al., 2016; Paukert et al., 2016).

Compared to groundwater, effects of precipitation on stream temperature are infrequently studied. Precipitation is rarely included as an explanatory variable in stream temperature models (Snyder et al., 2015), perhaps because potential processes through which precipitation affects water temperature (e.g., changes in timing and magnitude of surface runoff delivered to channels, reduced relative influence of groundwater inputs on temperature, changes in turbidity)

are indirect and difficult to measure. As such, the effects of climate change on precipitation, and resultant effects on stream temperature, have not been widely studied. In the Great Lakes region, climate change is expected to increase the frequency and intensity of precipitation events, particularly during winter and spring (Cherkauer & Sinha, 2010; Hayhoe et al., 2014), with potential effects on stream temperature (e.g., precipitation increases the discharge and volume of water exposed to solar radiation, causing temperatures to decrease or rise at a slower rate; precipitation increases sediment erosion, water turbidity, and absorption of solar radiation, causing temperatures to rise; Merriam et al., 2017). However, the extent to which precipitation regimes in a changing climate will affect groundwater recharge and associated thermal buffering in coldwater streams, and the degree to which managers can influence these relationships via water and land use management practices to sustain coldwater fisheries, have not been thoroughly investigated in the Great Lakes region.

The State of Michigan has a diversity of coldwater stream ecosystems that experience different air temperature patterns and hydrological regimes (i.e., groundwater/surface-runoff dominance) and currently support productive trout fisheries that are recreationally and culturally renowned. Hence, Michigan was an ideal study area for addressing our goal: to develop an accurate, cost-effective, management-relevant approach for modeling effects of changes in air temperature, precipitation, and groundwater on coldwater stream temperatures and trout survival and growth to help fisheries professionals sustainably manage trout populations amid climate change. Our objectives were to: 1) create stream-specific regression models that account for the influence of air temperature, precipitation patterns, and groundwater input on coldwater stream temperatures in Michigan; 2) compare precipitation- and groundwater-corrected models to simple air-stream temperature models in terms of accuracy (i.e., exactness of temperature

projection); and, 3) use precipitation- and groundwater-corrected models to predict effects of climate change on stream temperature and thermal habitat suitability for trout survival and growth out to the year 2056.

Methods

Study area

This study included coldwater streams (n = 15) containing trout populations located throughout the State of Michigan (Figure 4.1). These streams were distributed across most of Michigan from north to south (46.41°N to 42.64°N) to encompass latitudinal variation in air temperatures and thus stream thermal regimes. In addition, these streams spanned a hydrological gradient from groundwater to surface runoff dominance, which was evaluated according to base flow index, the proportion of streamflow represented by groundwater. Base flow index was calculated using a digital filter hydrograph separation method described by Neff et al. (2005). Streams were partitioned according to base flow index as: groundwater-dominated (base flow index > 0.60; surface-runoff dominated (hereafter "runoff-dominated"; base flow index < 0.60); and intermediate groundwater input (base flow index = 0.60; McKergow et al., 2005; Dukić & Mihailović, 2012). Moreover, all streams were significant for Michigan fisheries management because they contained viable, productive populations of brook trout (n = 9 streams), brown trout (n = 11), and rainbow trout (n = 9). These coldwater species are threatened by climate change (Carlson et al., 2016; Merriam et al., 2017) and distributed throughout 31,000 km of streams in Michigan, making them suitable indicator species for predicting how warmer water temperatures will affect stream fishes in groundwater-dominated and runoff-dominated systems.

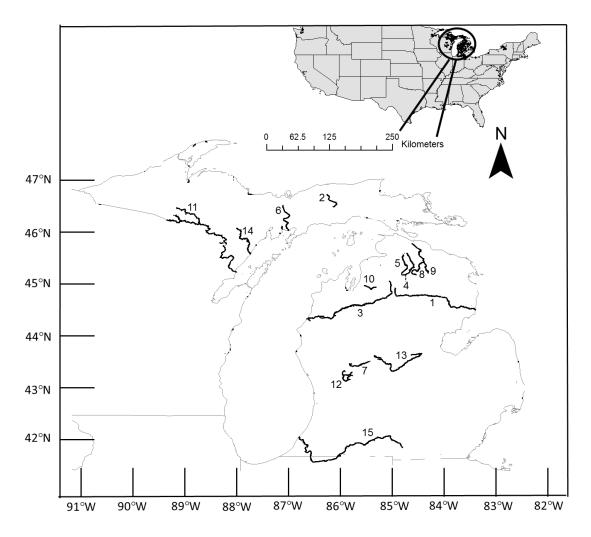


FIGURE 4.1. Map of 15 trout streams used for water temperature modeling in Michigan. Streams and corresponding identification numbers are listed in Table 4.1.

Temperature and precipitation measurements

Water temperature was measured hourly throughout July and August 2016 and 2017 in headwater portions of all 15 streams. These months were selected because they are generally the warmest and most thermally stressful for Michigan stream trout (Zorn et al., 2011) and would likely encompass the period during which predicted climatic changes would most strongly affect thermal habitat quality and quantity in this region. Moreover, headwater reaches were selected because they are typically the coolest, most thermally optimal habitats for trout during warm summer months in Michigan (Hayes et al., 1998); if they become warmer, temperatures in downstream reaches will also generally increase. Water temperature was measured using HOBO Pro v2 data loggers that are accurate within 0.2°C and have a drift of <0.1°C every year (Onset Computer Corporation, 2009). Data loggers were installed in habitats of intermediate velocity and depth, and were shielded from debris and direct sunlight using white polyvinyl chloride (PVC) pipes. Water was allowed to flow into the pipes through a series of holes. Hourly water temperatures were used to calculate the mean daily stream temperature (MDST) as a 24-h average. Hourly water temperatures were also measured in 2018 and are expressed as MDST values in Appendix 4.1.

Hourly air temperatures and daily precipitation measurements were collected throughout the study period using the Michigan State University Enviro-weather Automated Weather Station Network (EAWSN, 2018) at stations within each stream's watershed. Hourly air temperature data were summarized as mean daily air temperatures (MDAT) for each stream reach. Likewise, precipitation measurements were summarized as cumulative daily precipitation for each reach.

Temperature projections

Three coupled climate models were used to project future (i.e., 2036, 2056) July and August air temperatures in each stream reach studied. These models included the Third Generation Coupled Global Climate Model (CGCM3, Canadian Centre for Climate Modelling and Analysis), the CM2 Global Coupled Climate Model (CM2, Geophysical Fluid Dynamics Laboratory at the National Oceanic and Atmospheric Administration), and the Hadley Centre Coupled Model version 3 (HadCM3, Met Office, United Kingdom's National Weather Service). These models were selected because they differ in their thermal input parameters (e.g. solar radiation, trace gases, sulfate aerosols), thereby encompassing a range of climatic conditions that Michigan streams could experience in the future. However, all coupled climate models were based on the World Climate Research Programme (WCRP) Coupled Model Intercomparison Project phase 3 (CMIP3) multi-model dataset. The spatial resolution of climate models (~200 x 200 km) was downscaled to a level relevant for Michigan streams (12 x 12 km; Maurer et al., 2007) using the Bias-Correction Spatial Disaggregation approach. Projected air temperatures were supplied by the United States Forest Service Eastern Forest Environmental Threat Assessment Center in North Carolina, USA, and calculated using the A2 (820 ppm atmospheric CO2 by 2100) and B1 (550 ppm atmospheric CO2 by 2100) climate forcing scenarios from the Special Report of Emission Scenarios (IPCC, 2007). Modeling air temperatures under A2 and B1 conditions represented upper and lower CO2 emission thresholds for stream temperature prediction.

Air temperature predictions from coupled climate models were used to define three modeled air temperature warming (MATW) increments (+1.7°C, +3.4°C, +5.1°C) for projecting future MDSTs. These increments covered the range of predicted air temperature increases for

Michigan over the next 40 years (Carlson et al., 2016). Stream temperatures were projected under different prevailing weather conditions by applying MATW increments to both 2016 (relatively warm, dry) and 2017 (relatively cool, wet) air temperatures (EAWSN, 2018). These conditions were useful for forecasting future stream thermal regimes because they represented weather extremes for Michigan streams under predicted changes in climate (i.e., temperature, precipitation; Primack, 2000; Parry et al., 2007; Stoner et al., 2013).

Stream temperature models and projections

Least-squares linear regression was used to model MDST as a function of MDAT, groundwater, and precipitation. Initial modeling focused on stream-specific relationships between MDST and MDAT. Streams generally warmed throughout summer, but varied in the degree to which MDST was correlated with MDAT, indicating stream-specific variability in how groundwater and precipitation affect stream temperature. Hence, in addition to MDAT, thermal effects of groundwater input and precipitation were modeled.

In groundwater-dominated streams, the thermal influence of groundwater was calculated as accumulated degree-days above mean summer air temperature (ADD) because it is directly related to summer ground surface temperature, the driver of groundwater temperature during this time year (Kurylyk et al., 2013). Previous researchers have successfully used ADD to incorporate groundwater dynamics into stream temperature modeling in the eastern United States (Snyder et al., 2015). The ADD approach is readily applicable in groundwater-dominated Michigan streams and offers benefits for resource managers (e.g., accuracy along with practicality and inexpensive data collection) compared to complex heat budget models that require detailed atmospheric, meteorological, and hydrological data for a limited number of sites (Webb et al., 2008). Stream temperature models for groundwater-dominated streams took the following form:

$$MDST_i = m_1 * MDAT_i + m_2 * ADD_i + b_0$$
(1)

where MDST_{*i*} is projected MDST (°C) on day *i*, MDAT_{*i*} is projected MDAT (°C) on day *i*, ADD_{*i*} is the ADD (degree-days) on day *i*, m_1 and m_2 are regression coefficients, and b_0 is the model intercept.

In runoff-dominated streams, MDST was modeled as a function of MDAT and precipitation according to the following formula:

$$MDST_i = m_1 * MDAT_i + m_2 * PR_i + b_0$$
(2)

where PR_{*i*} is the cumulative precipitation (since July 1) on day *i* and other model components are the same as above. Models including ADD were applied to runoff-dominated streams and those including precipitation were applied to groundwater-dominated streams, but these models were not sufficiently parsimonious (according to bias-corrected Akaike's information criterion [AICc], see Analyses section below) to warrant further consideration. In addition, both ADD and precipitation models were applied to streams with intermediate groundwater input, but their relatively high AICc scores (i.e., low parsimony) compared to MDAT-only models rendered it statistically appropriate to model water temperatures in these streams with MDAT alone.

Effects of groundwater inputs and precipitation on stream temperatures under projected climate change scenarios may not be the same as those that currently occur (Kurylyk et al., 2013; Menberg et al., 2014). For example, although the amount of precipitation may remain relatively stable in summer, as predicted for Michigan under both high and low CO₂ emissions scenarios

(Hayhoe et al., 2014), the temperature of precipitation (or groundwater) may change in a warming climate. Hence, we modeled effects of changes in thermal sensitivity of groundwater (TS_{gw} ; change in groundwater temperature per 1°C air temperature increase; Snyder et al., 2015) and thermal sensitivity precipitation (TS_{pr} ; change in precipitation temperature per 1°C air temperature increase) on future stream temperatures. In practice, this involves increasing model *y*-intercepts by the product of MATW and TS_{gw} (in groundwater-dominated streams; Snyder et al., 2015) or TS_{pr} (in runoff-dominated streams). The stream-specific *y*-intercept increase is a function of TS_{gw} or TS_{pr} and the proportion of streamflow comprised of groundwater (R^2_{ADD}) or precipitation (R^2_{PR}), calculated as:

$$R_{ADD}^{2} = \left[m_{2}\left(\frac{S_{ADD}}{S_{MDST}}\right)\right] * \left[\left(\frac{1}{n-1}\right)\sum_{i=1}^{n}\left(\frac{ADD_{i}-\overline{ADD}}{S_{ADD}}\right) * \left(\frac{MDST_{i}-\overline{MDST}}{S_{MDST}}\right)\right]$$
(3)

where m_2 is regression coefficient for the ADD_i term in (1), S_{ADD} is the standard deviation of ADD, S_{MDST} is the standard deviation of MDST, n is the number of days, ADD_i is the ADD at day i, \overline{ADD} is the mean ADD, MDST_i is the MDST at day i, and \overline{MDST} is the mean MDST (Snyder et al., 2015). Similarly, R^2_{PR} was calculated as:

$$R_{PR}^{2} = \left[m_{2}\left(\frac{S_{PR}}{S_{MDST}}\right)\right] * \left[\left(\frac{1}{n-1}\right)\sum_{i=1}^{n}\left(\frac{PR_{i}-\overline{PR}}{S_{PR}}\right) * \left(\frac{MDST_{i}-\overline{MDST}}{S_{MDST}}\right)\right]$$
(4)

where m_2 is the regression coefficient for PR_i (cumulative precipitation since July 1) in (2), S_{PR} is the standard deviation of PR, S_{MDST} is the standard deviation of MDST, *n* is the number of days, PR_i is the PR at day *i*, \overline{PR} is the mean PR, MDST_i is the MDST at day *i*, and \overline{MDST} is the mean MDST. To incorporate R^{2}_{ADD} and R^{2}_{PR} into stream temperature models, linear regressions were developed between model *y*-intercepts and R^{2}_{ADD} (for groundwater-dominated streams) and *y*-intercepts and R^{2}_{PR} values (for runoff-dominated streams):

$$b_0 = 8.20 + (10.03 * R_{ADD}^2) + e$$

$$b_0 = 4.29 + (14.75 * R_{PR}^2) + e$$
(5)

These models explained 68% and 72% of the variation in model *y*-intercepts, respectively, and residuals were uncorrelated and randomly distributed around zero. Hence, these models were considered suitable for use in stream temperature projection (Snyder et al., 2015). To model how changes in air temperature, TS_{gw}, and TS_{pr} would affect model *y*-intercepts, the following equations were used for groundwater-dominated and runoff-dominated streams:

$$B_{0adj} = 8.20 + \left[\left(10.03 + \left(MATW * TS_{gw} \right) \right) * R_{ADD}^{2} \right] + e$$

$$B_{0adj} = 4.29 + \left[\left(14.75 + \left(MATW * TS_{pr} \right) \right) * R_{PR}^{2} \right] + e$$
(7)

In turn, these adjusted model *y*-intercepts were used in place of those in equations (1) and (2) to predict stream-specific MDST under different climate change scenarios:

$$MDST_{i} = m_{1}MDAT_{i} + m_{2}ADD_{i} + B_{0adj}$$
(9)

$$MDST_i = m_1 MDAT_i + m_2 PR_i + B_{0adj}$$

(10)

(8)

(6)

Stream temperatures were modeled under three TS_{gw} and TS_{pr} conditions (0.0, 0.66, 1.0) that span a range from insensitive streams (i.e., groundwater and precipitation temperature do not change substantially with air temperature) to highly sensitive streams (i.e., groundwater and precipitation temperature change in proportion to air temperature). The 0.0 condition was included as a reference point and is likely less realistic than 0.66 and 1.0, which encompass values reported or used in recent studies (Kurylyk et al., 2013; Snyder et al., 2015). Adjusted multiple regression models (Eq. 7, 8) were used to project MDST in each stream reach based on all combinations of MATW (+1.7°C, +3.4°C, +5.1°C) and TS_{gw}/TS_{pr} (0.0, 0.66, 1.0).

Stream thermal sensitivity – the increase in stream temperature resulting from a 1.0° C air temperature increase (Snyder et al., 2015) – was also evaluated for each stream under three TS_{gw} conditions. Stream thermal sensitivity measurements were derived by first calculating stream-specific mean summer water temperatures from baseline (i.e., 2016, 2017) data. These values were subtracted from MDSTs calculated using equations (9) and (10) under 1.0° C air temperature warming compared to baseline temperatures. The difference between these two values was treated as an empirical measurement of stream thermal sensitivity (Snyder et al., 2015).

Thermal habitat suitability predictions

Stream-specific temperature projections were compared with temperature ranges for trout survival and growth to assess future thermal habitat suitability under different combinations of MATW and TS_{gw}/TS_{pr} . Temperature thresholds (i.e., thermal minima, maxima) were defined in reference to juvenile trout (if they differed from those of adults) under the premise that resilient trout fisheries can only be conserved if young fish survive to adulthood. Streams with optimal

trout growing conditions were those that had mean July-August temperatures ranging from 11.0 $^{\circ}$ C to 16.4 $^{\circ}$ C (brook trout; Baldwin, 1957; Raleigh, 1982a), 12.0 $^{\circ}$ C to 16.9 $^{\circ}$ C (brown trout; Hay et al. 2006), and 12.0 $^{\circ}$ C to 16.3 $^{\circ}$ C (rainbow trout; Wurtsbaugh and Davis 1977; Raleigh 1982b). Streams with suitable (but not optimal) temperatures for trout growth ranged from 16.5 $^{\circ}$ C to 20.4 $^{\circ}$ C (brook trout; Baldwin, 1957; Raleigh, 1982a), 17.0 $^{\circ}$ C to 19.9 $^{\circ}$ C (brown trout; Hay et al. 2006), and 16.4 $^{\circ}$ C to 22.4 $^{\circ}$ C (rainbow trout; Wurtsbaugh and Davis 1977; Raleigh 1982b). Streams that were too varm for trout growth in July-August had temperatures ranging from 20.5 $^{\circ}$ C to 25.2 $^{\circ}$ C (brook trout; Baldwin, 1957; Raleigh, 1982a), 20.0 $^{\circ}$ C to 26.1 $^{\circ}$ C (brown trout; Hay et al. 2006), and 22.5 $^{\circ}$ C to 24.9 $^{\circ}$ C (rainbow trout; Wurtsbaugh and Davis 1977; Raleigh 1982b). Finally, streams that were too warm for trout survival in July-August had temperatures 2 25.3 $^{\circ}$ C (brook trout; Fry et al. 1946; Raleigh 1982a), 26.2 $^{\circ}$ C (brown trout; Hay et al. 2006), and 25.0 $^{\circ}$ C (rainbow trout; Wurtsbaugh and Davis 1977; Raleigh 1982b). These temperature ranges were used to calculate the proportion of streams studied that would remain suitable for trout survival and growth under alternative climate change scenarios.

Analyses

Four stream temperature models (i.e., MDAT, MDAT + ADD, MDAT + precipitation, MDAT + ADD + precipitation) were developed and compared for each stream using information-theoretic model selection and bias-corrected AICc (Burnham & Anderson, 2002). Invariably, groundwater-dominated streams were modeled most accurately (i.e., lowest AICc scores, Δ AICc generally >> 2) with the groundwater model (MDAT + ADD) and runoffdominated streams with the precipitation model (MDAT + precipitation), thus equations (9) and (10) were applied to these stream types. Models including both ADD and precipitation were occasionally within two AICc units of top-supported models, wherein the additional parameter (relative to the top-performing model) was uninformative (i.e., did not reduce model deviance) such that interpreting the extra parameter would have caused modeling bias (Burnham & Anderson, 2001; Arnold, 2010). Hence, by only including the top model for each stream, all models received substantial AICc support and only contained informative parameters (i.e., those that reduced model deviance). All analyses were performed in RStudio Desktop version 1.1.423 (RStudio, 2015).

Results

Stream temperature models and thermal sensitivity

Relationships between MDAT and MDST were highly variable among the Michigan coldwater streams evaluated (Table 4.1). Air and stream temperatures were positively correlated in runoff-dominated systems (e.g., Paint River; $R^2 = 0.86$; Figure 4.2a) and in streams with intermediate groundwater input (e.g., Tamarack Creek; $R^2 = 0.55$; Figure 4.2b) but not significantly correlated in groundwater-dominated streams (e.g., East Branch Fox River; $R^2 = 0.09$; Figure 4.2c). Temperatures in most streams (87%) were modeled most accurately (i.e., lowest AICc values) by combining ADD and MDAT in groundwater-dominated streams and precipitation and MDAT in runoff-dominated streams. Including ADD and precipitation improved model accuracy, with adjusted R^2 values increasing by 0.06–0.75 (Table 4.1, Figure 4.3a, b, c). Models including ADD and precipitation had an average adjusted R^2 of 0.83 (range 0.75–0.95), compared to 0.58 (range 0.06–0.80) for unadjusted models with only MDAT (Table 4.1, Figure 4.4). Water temperatures in streams with intermediate groundwater input (i.e., Pigeon

TABLE 4.1. Michigan stream information and model parameters. Map number refers to stream identifiers in Figure 4.1. BFI represents base flow index, the mean rate of base flow divided by the corresponding mean rate of total streamflow (Neff et al. 2005). Species denotes the trout species present in each stream (BKT [brook trout], BNT [brown trout], RBT [rainbow trout], All [all three species]). Year denotes the baseline year and corresponding weather conditions (2016: warm, dry; 2017: cool, wet) from which the model was developed. Other abbreviations denote model intercepts (Int); coefficients for mean daily air temperature (MDAT), accumulated degree-days above mean summer air temperature (ADD, a measure of groundwater input), and cumulative daily precipitation since July 1 (PR); *P* values; bias-corrected Akaike's information criterion scores (AICc); adjusted R^2 values (Adj R^2) for groundwater- and precipitation-corrected models; and adjusted R^2 values for MDAT-only models (MDAT Adj R^2).

Stream	Мар	BFI	Species	Year	Int	MDAT	ADD	PR	Р	AICc	Adj R^2	MDAT Adj R ²
Au Sable R.	1	0.67	All	2016	15.91	0.14	-0.06		< 0.01	43.80	0.79	0.60
				2017	14.45	0.18	-0.05		< 0.01	38.67	0.84	0.70
E. Branch Fox R.	2	0.61	BKT, BNT	2016	11.13	0.12	-0.04		< 0.01	19.29	0.75	0.46
				2017	10.64	0.02	-0.03		< 0.01	36.87	0.75	0.10
Manistee R.	3	0.61	All	2016	14.38	0.20	-0.08		< 0.01	51.55	0.80	0.62
				2017	15.53	0.09	-0.06		< 0.01	41.25	0.77	0.71
Pigeon R.	4	0.60	BNT, RBT	2016	10.52	0.14			< 0.01	47.04	0.56	
				2017	9.08	0.21			< 0.01	77.94	0.58	
W Br Sturgeon R.	5	0.60	All	2016	9.86	0.18			< 0.01	57.76	0.45	
				2017	9.45	0.19			< 0.01	87.34	0.52	
Sturgeon R.	6	0.59	BKT, RBT	2016	14.04	0.40		-0.64	< 0.01	75.86	0.89	0.64
				2017	13.35	0.35		-0.55	< 0.01	100.93	0.86	0.65
Tamarack Creek	7	0.55	BNT, RBT	2016	15.23	0.47		-0.52	< 0.01	40.23	0.90	0.55
				2017	11.37	0.37		-0.31	< 0.01	54.86	0.88	0.80
Black R.	8	0.51	BKT	2016	11.98	0.22		-0.40	< 0.01	33.69	0.83	0.77
				2017	8.42	0.22		-0.60	< 0.01	51.52	0.85	0.72
Canada Creek	9	0.51	BKT	2016	15.72	0.11		-0.71	< 0.01	49.40	0.78	0.55
				2017	14.22	0.21		-0.60	< 0.01	59.42	0.75	0.62

TABLE 4.1 (cont'd).

Stream	Map	BFI	Species	Year	Int	MDAT	ADD	PR	Р	AICc	Adj R^2	MDAT Adj R ²
Rapid R.	10	0.50	All	2016	11.55	0.08		-1.44	< 0.01	25.72	0.85	0.47
				2017	11.76	0.04		-2.51	< 0.01	69.46	0.84	0.49
Paint R.	11	0.49	BNT	2016	18.50	0.32		-0.76	< 0.01	46.37	0.95	0.72
				2017	21.00	0.18		-1.09	< 0.01	67.65	0.81	0.06
Rogue R.	12	0.47	BNT, RBT	2016	20.28	0.14		-0.46	< 0.01	77.50	0.83	0.57
				2017	16.83	0.22		-1.57	< 0.01	69.38	0.84	0.66
Pine R.	13	0.44	BNT	2016	15.58	0.08		-0.20	< 0.01	37.06	0.75	0.50
				2017	13.18	0.06		-0.93	< 0.01	31.03	0.79	0.43
Cedar R.	14	0.38	BNT	2016	14.60	0.27		-0.68	< 0.01	51.24	0.77	0.57
				2017	12.76	0.35		-0.63	< 0.01	74.87	0.87	0.74
St Joe R.	15	0.35	BKT, RBT	2016	17.56	0.23		-0.62	< 0.01	19.65	0.86	0.71
				2017	15.96	0.28		-1.20	< 0.01	62.32	0.89	0.76

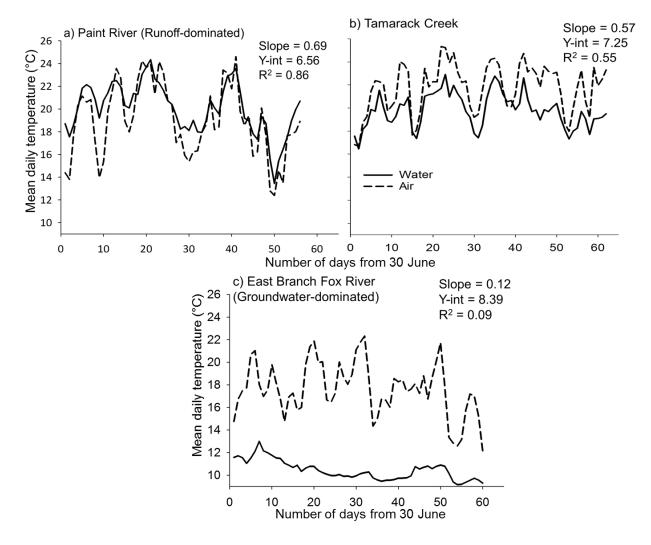


FIGURE 4.2. Relationships between predicted mean daily water temperature and observed mean daily air temperature for Michigan trout streams. Graphs (a), (b), and (c) display examples that span the range of air-stream temperature relationships and corresponding regression statistics (including slope, y-intercept, adjusted R^2) observed in this study.

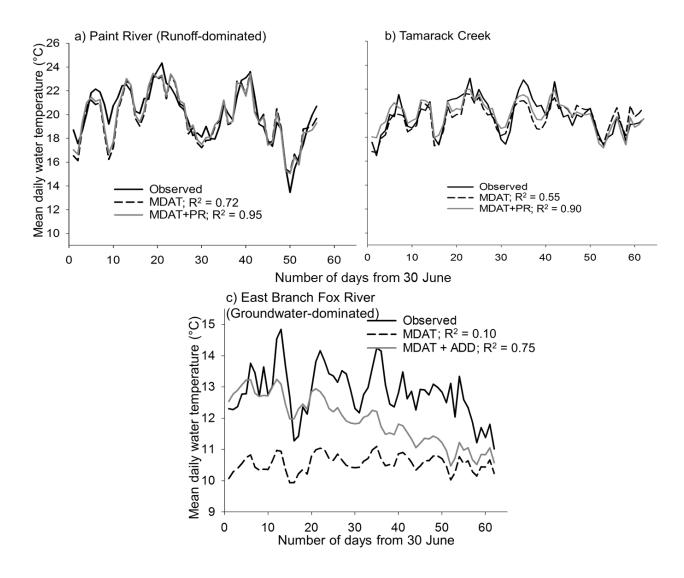


FIGURE 4.3. Comparison of predictions of mean daily water temperature in Michigan streams between linear regressions that used only mean daily air temperature (MDAT) as an independent variable, and models that used both MDAT and an additional predictor (i.e., accumulated degreedays above mean summer air temperature [ADD], cumulative daily precipitation since July 1 [PR]). Graphs (a), (b), and (c) show streams spanning a gradient of baseflow from runoffdominated to groundwater-dominated and encompassing the range of air-stream temperature relationships observed in this study. R^2 values are adjusted R^2 .

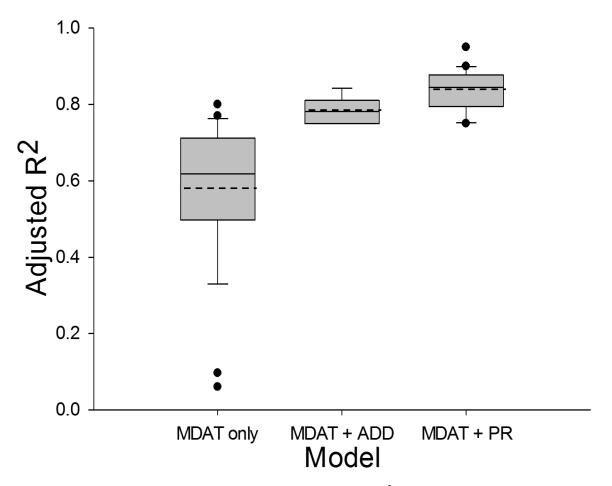


FIGURE 4.4. Comparison of the distribution of adjusted R^2 values for Michigan stream temperature linear regressions that used only mean daily air temperature (MDAT only) as an independent variable, and models that used both MDAT and an additional predictor (i.e., accumulated degree-days above mean summer air temperature [ADD], cumulative daily precipitation since July 1 [PR]).

River, West Branch Sturgeon River) were modeled most accurately with MDAT alone (Table 4.1). These findings suggest that fisheries managers should model groundwater-dominated stream temperatures with ADD and MDAT, runoff-dominated stream temperatures with precipitation and MDAT, and temperatures of streams with intermediate groundwater input with MDAT alone.

Stream thermal sensitivity tended to decline with increasing groundwater input but was highly influenced by TSgw conditions. The decrease in stream thermal sensitivity with increasing groundwater input was most pronounced for TSgw = 0 (Figure 4.5a) and considerably weaker for TSgw = 0.66 (Figure 4.5b). For TSgw = 1.00, thermal sensitivity remained stable regardless of groundwater input (Figure 4.5c), indicating removal of groundwater-driven temperature buffering and thus less favorable thermal conditions for trout survival and growth.

Stream temperature projections

Projected future water temperatures in Michigan coldwater streams varied among climate change scenarios (i.e., combinations of MATW and TS_{gw}/TS_{pr}) and between baseline weather conditions (i.e., warm/dry, cool/wet) used to construct stream temperature models. In warm, dry conditions, projected stream temperatures warmed as both MATW and TS_{gw}/TS_{pr} increased (Table 4.2). In groundwater-dominated streams, mean projected stream temperature across TS_{gw} categories was 16.58°C for MATW = 1.7°C, 17.36°C for MATW = 3.4°C, and 18.15°C for MATW = 5.1°C (Figure 4.6). Within all MATW categories, predicted groundwater-dominated stream temperatures warmed as TS_{gw} increased. The magnitude of this warming increased as MATW intensified from +1.7°C (0.94°C) to +3.4°C (1.88°C) and +5.1°C (2.82°C; Figure 4.6). These results indicate that in warm, dry future weather conditions, water temperatures in

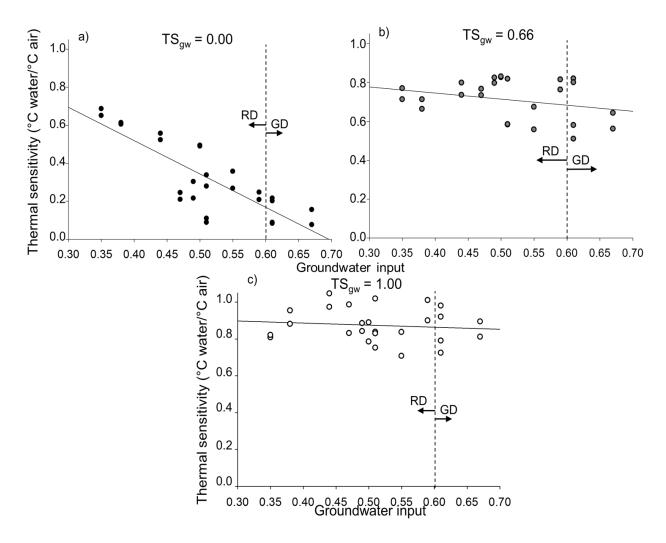


FIGURE 4.5. Relationships between modeled stream thermal sensitivity (°C water/°C air) and groundwater input for the 13 Michigan streams best modeled with MDAT + PR (surface runoff-dominated [RD] streams) and MDAT + ADD (groundwater-dominated [GD] streams). Graphs (a), (b), and (c) display stream thermal sensitivities for three conditions of increasing groundwater thermal sensitivity ($TS_{gw} = 0.0, 0.66, 1.0$). Dotted lines denote transitions between RD and GD streams.

TABLE 4.2. Michigan stream temperatures and projected future temperatures in three conditions of modeled air temperature warming $(+1.7^{\circ}C, +3.4^{\circ}C, +5.1^{\circ}C)$ and thermal sensitivity of groundwater/precipitation (0.0, 0.66, 0.1; in parentheses) based on 2016 weather conditions (i.e., warm, dry).

Stream	2016	+1.7(0)	+1.7(0.66)	+1.7(1)	+3.4(0)	+3.4(0.66)	+3.4(1)	+5.1(0)	+5.1(0.66)	+5.1(1)
Au Sable R.	17.25	17.50	18.33	18.75	17.73	19.39	20.24	17.97	20.45	21.73
E. Branch Fox R.	12.79	13.14	13.48	13.66	13.35	14.04	14.40	13.56	14.60	15.14
Manistee R.	17.22	17.55	18.23	18.58	17.89	19.26	19.96	18.23	20.29	21.34
Pigeon R.	13.54	13.78	13.78	13.78	14.02	14.02	14.02	14.26	14.26	14.26
W Br Sturgeon R.	13.65	13.95	13.95	13.95	14.25	14.25	14.25	14.55	14.55	14.55
Sturgeon R.	23.81	24.30	25.04	25.42	24.97	26.45	27.21	25.64	27.87	29.01
Tamarack Creek	19.80	20.87	21.82	22.31	21.67	23.57	24.55	22.48	25.32	26.79
Black R.	15.91	16.35	17.16	17.59	16.71	18.35	19.19	17.08	19.53	20.80
Canada Creek	16.99	17.26	18.10	18.53	17.44	19.12	19.99	17.62	20.15	21.45
Rapid R.	12.87	13.30	13.87	14.17	13.43	14.58	15.17	13.56	15.28	16.17
Paint R.	22.94	23.38	24.37	24.87	23.92	25.90	26.91	24.46	27.43	28.95
Rogue R.	22.08	22.38	23.26	23.72	22.61	24.39	25.30	22.85	25.51	26.88
Pine R.	16.92	17.24	18.03	18.43	17.38	18.95	19.76	17.51	19.87	21.08
Cedar R.	19.25	19.68	20.48	20.89	20.14	21.73	22.55	20.59	22.98	24.22
St Joe R.	22.28	22.61	23.51	23.97	23.00	24.80	25.72	23.40	26.09	27.48

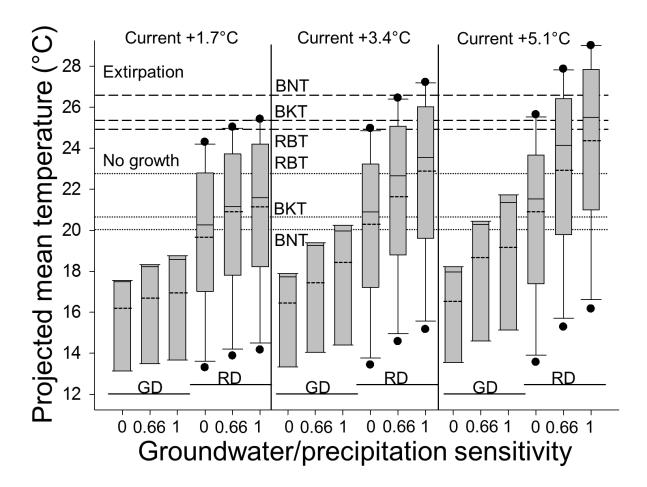


FIGURE 4.6. Distribution of projected mean daily water temperatures based on 2016 weather conditions (warm, dry) in three conditions of modeled air temperature warming $(+1.7^{\circ}C, +3.4^{\circ}C, +5.1^{\circ}C)$ and thermal sensitivity of groundwater/precipitation (0.0, 0.66, 0.1) for the 13 Michigan streams best modeled with MDAT + PR and MDAT + ADD. Within each box plot, small dashed lines are means and solid lines are medians. Long dashed lines spanning the entire panel represent upper thermal thresholds for brook trout (BKT), brown trout (BNT), and rainbow trout (RBT), whereas long dotted lines denote upper thermal thresholds for growth.

groundwater-dominated Michigan streams will rise in proportion to the magnitude of air temperature warming and groundwater thermal sensitivity amid climate change. However, predicted increases in groundwater-dominated stream temperatures will be small relative to those projected for runoff-dominated streams studied herein.

In runoff-dominated streams under warm, dry weather conditions, projected water temperatures were appreciably higher than those in groundwater-dominated systems (Figure 4.6) despite similar trajectories of thermal change (i.e., stream temperatures increase in proportion to MATW and TS_{pr} ; Table 4.2). In runoff-dominated streams, mean projected stream temperature across TS_{pr} categories was 20.43°C for MATW = 1.7°C, 21.52°C for MATW = 3.4°C, and 22.60°C for MATW = 5.1°C (Figure 4.6). Predicted runoff-dominated stream temperatures warmed in proportion to TS_{pr} within MATW categories. As in groundwater-dominated streams, the magnitude of this increase became larger in runoff-dominated systems as MATW increased from +1.7°C (1.25°C) to +3.4°C (2.51°C) and +5.1°C (3.76°C; Figure 4.6). These findings suggest that in warm, dry future weather conditions, water temperatures in runoff-dominated Michigan streams will increase more than those in groundwater-dominated streams while following a similar proportional relationship with the magnitude of air temperature warming and groundwater thermal sensitivity in a changing climate.

In cool, wet weather conditions, projected stream temperatures were lower than those predicted in warm, dry conditions (Figure 4.6, 4.7). However, temperatures warmed with increasing MATW and TS_{gw}/TS_{pr} (Table 4.3). In groundwater-dominated streams, mean projected stream temperature across TS_{gw} categories was 15.15°C for MATW = 1.7°C, 15.88°C for MATW = 3.4°C, and 16.61°C for MATW = 5.1°C (Figure 4.7). Predicted groundwater-dominated stream temperatures warmed as TS_{gw} increased within all MATW categories. The

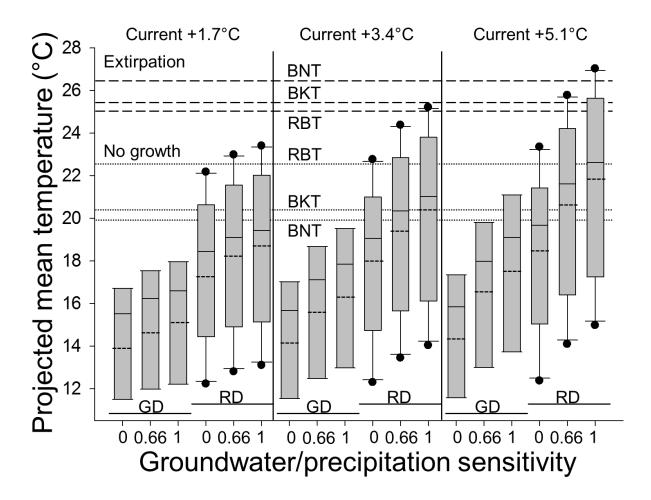


FIGURE 4.7. Distribution of projected mean daily water temperatures based on 2017 weather conditions (cool, wet) in three conditions of modeled air temperature warming $(+1.7^{\circ}C, +3.4^{\circ}C, +5.1^{\circ}C)$ and thermal sensitivity of groundwater/precipitation (0.0, 0.66, 0.1) for the 13 Michigan streams best modeled with MDAT + PR and MDAT + ADD. Within each box plot, small dashed lines are means and solid lines are medians. Long dashed lines spanning the entire panel represent upper thermal thresholds for brook trout (BKT), brown trout (BNT), and rainbow trout (RBT), whereas long dotted lines denote upper thermal thresholds for growth.

TABLE 4.3. Michigan stream temperatures and projected future temperatures in three conditions of modeled air temperature warming $(+1.7^{\circ}C, +3.4^{\circ}C, +5.1^{\circ}C)$ and thermal sensitivity of groundwater/precipitation (0.0, 0.66, 0.1; in parentheses) based on 2017 weather conditions (i.e., cool, wet).

Stream	2017	+1.7(0)	+1.7(0.66)	+1.7(1)	+3.4(0)	+3.4(0.66)	+3.4(1)	+5.1(0)	+5.1(0.66)	+5.1(1)
Au Sable R.	16.52	16.72	17.55	17.97	17.03	18.68	19.53	17.34	19.82	21.09
E. Branch Fox R.	10.86	11.51	11.98	12.22	11.55	12.49	12.98	11.59	13.00	13.73
Manistee R.	15.37	15.52	16.24	16.61	15.68	17.12	17.86	15.84	18.00	19.11
Pigeon R.	12.90	13.18	13.18	13.18	13.53	13.53	13.53	13.88	13.88	13.88
W Br Sturgeon R.	12.81	13.10	13.10	13.10	13.43	13.43	13.43	13.75	13.75	13.75
Sturgeon R.	21.76	22.17	22.98	23.40	22.76	24.38	25.21	23.35	25.77	27.02
Tamarack Creek	17.84	18.59	19.09	19.35	19.23	20.23	20.75	19.86	21.36	22.14
Black R.	14.33	14.79	15.12	15.29	15.15	15.82	16.16	15.52	16.52	17.03
Canada Creek	16.91	17.17	17.97	18.39	17.52	19.13	19.96	17.86	20.29	21.54
Rapid R.	11.85	12.23	12.80	13.10	12.30	13.44	14.03	12.37	14.09	14.97
Paint R.	21.21	21.65	22.53	22.99	21.96	23.73	24.64	22.27	24.93	26.30
Rogue R.	19.51	20.32	21.24	21.71	20.69	22.53	23.48	21.06	23.82	25.24
Pine R.	13.04	13.40	14.22	14.64	13.50	15.13	15.98	13.59	16.05	17.32
Cedar R.	18.11	18.30	19.09	19.50	18.89	20.49	21.31	19.49	21.88	23.11
St Joe R.	19.80	20.20	21.15	21.63	20.67	22.56	23.53	21.15	23.97	25.43

magnitude of this increase became larger as MATW increased from +1.7°C (1.02°C) to +3.4°C (2.03°C) and +5.1°C (3.05°C; Figure 4.7). These results indicate that in cool, wet future weather conditions, water temperatures of groundwater-dominated Michigan streams will rise in proportion to the magnitude of air temperature warming and groundwater thermal sensitivity amid climate change. Nevertheless, predicted increases in groundwater-dominated stream temperatures will be small relative to: 1) those predicted for groundwater-dominated streams in warm, dry weather conditions; and 2) those projected for runoff-dominated streams in cool, wet weather conditions.

In runoff-dominated streams under cool, wet weather conditions, projected water temperatures were higher than those in groundwater-dominated systems (Figure 4.7) notwithstanding similar trajectories of thermal change (i.e., stream temperatures increase in proportion to MATW and TS_{pr}; Table 4.3). Mean projected stream temperature across TS_{pr} categories in runoff-dominated streams was 18.50°C for MATW = 1.7°C, 19.50°C for MATW = 3.4°C, and 20.51°C for MATW = 5.1°C (Figure 4.7). Predicted runoff-dominated stream temperatures warmed as TS_{pr} increased within MATW categories. As in groundwater-dominated streams, the magnitude of this increase became larger in runoff-dominated systems as MATW increased from +1.7°C (1.12°C) to +3.4°C (2.24°C) and +5.1°C (3.36°C; Figure 4.7). These findings suggest that in cool, wet future weather conditions, water temperatures in runoffdominated Michigan streams will increase in proportion to air temperature warming and groundwater thermal sensitivity in a changing climate. Such temperature changes will likely be large relative to those in groundwater-dominated streams in similar weather conditions but small relative to those in runoff-dominated streams in warm, dry conditions.

Thermal habitat suitability predictions

In 2016, all streams evaluated in this study had MDST that were suitable for survival of brook trout, brown trout, and rainbow trout. Most streams (73%, n = 11) had temperatures that were optimal or suitable for summer trout growth. Four runoff-dominated streams (Paint, Rogue, St. Joseph, and Sturgeon rivers) had temperatures that were unsuitable for summer growth of brook trout and brown trout, including two streams (Paint and Sturgeon rivers) that were unsuitable for rainbow trout growth (Table 4.2). Based on 2016 weather conditions (i.e., relatively warm, dry), thermal habitats in groundwater-dominated streams were predicted to be suitable for survival of all trout species regardless of MATW/TSgw conditions (Table 4.4, Figure 4.6). Projected groundwater-dominated stream temperatures were suitable for summer growth of rainbow trout in all MATW/TS_{gw} conditions, brook trout in all but one condition (MATW = 5.1°C, TS_{gw} = 1), and brown trout in all but three conditions (MATW = 3.4° C, TS_{gw} = 1; MATW $= 5.1^{\circ}$ C, TS_{gw} = 0.66; MATW = 5.1°C, TS_{gw} = 1; Table 4.2, 4.4, Figure 4.6). Hence, even if climate change results in warm, dry weather conditions, Michigan stream trout will continue to survive and generally maintain summer growth in the groundwater-dominated streams studied herein.

In warm, dry weather conditions, runoff-dominated streams became progressively less suitable for survival and growth of all trout species as MATW and TS_{pr} increased (Table 4.4, Figure 4.6). As MATW increased from +1.7°C to +5.1°C, the mean percentage of runoff-dominated streams suitable for brook trout survival and growth declined from 93% (survival) and 60% (growth) to 67% (survival) and 47% (growth). Likewise, the mean percentage of runoff-dominated streams suitable for brown trout survival and growth decreased from 100% (survival) and 39% (growth) to 77% (survival) and 28% (growth; Table 4.4, Figure 4.6).

TABLE 4.4. Thermal habitat suitability for brook trout (BKT), brown trout (BNT), and rainbow trout (RBT) survival and growth in Michigan streams based 2016 weather conditions (i.e., warm, dry). Table entries report the proportion of streams that are suitable for survival (numerator) and growth (denominator) in three conditions of modeled air temperature warming $(+1.7^{\circ}C, +3.4^{\circ}C, +5.1^{\circ}C)$ and thermal sensitivity of groundwater/precipitation (0.0, 0.66, 0.1; in parentheses). Streams are classified as groundwater-dominated (GD; base flow index > 0.60), runoff-dominated (RD; base flow index < 0.60), or systems with intermediate groundwater input (Int; base flow index = 0.60; Neff et al., 2005).

Species	Stream	+1.7(0)	+1.7(0.66)	+1.7(1)	+3.4(0)	+3.4(0.66)	+3.4(1)	+5.1(0)	+5.1(0.66)	+5.1(1)
BKT	GD (3)	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/0.33
	RD (5)	1/0.6	1/0.6	0.8/0.6	1/0.6	0.8/0.6	0.6/0.6	0.8/0.6	0.6/0.6	0.6/0.2
	Int (1)	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1
BNT	GD (3)	1/1	1/1	1/1	1/1	1/1	1/0.67	1/1	1/0.33	1/0.33
	RD (6)	1/0.5	1/0.33	1/0.33	1/0.33	1/0.33	0.83/0.33	1/0.33	0.83/0.33	0.5/0.17
	Int (2)	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1
RBT	GD (2)	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1
	RD (5)	1/0.6	0.8/0.4	0.8/0.4	1/0.4	0.8/0.2	0.4/0.2	0.8/0.4	0.2/0.2	0.2/0.2
	Int (2)	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1

Rainbow trout exhibited a similar trend, as 87% and 47% of runoff-dominated streams were suitable for survival and growth when MATW = $+1.7^{\circ}$ C, compared to 40% (survival) and 27% (growth) when MATW = $+5.1^{\circ}$ C. Streams with intermediate groundwater input (i.e., Pigeon and West Branch Sturgeon rivers) were projected to be suitable for survival and growth of all trout species in all MATW/TS_{pr} conditions (Table 4.4, Figure 4.6). Thus, in warm, dry future weather conditions, trout survival and growth will decrease in runoff-dominated Michigan streams to a greater degree than groundwater-dominated streams in similar weather conditions.

In relatively cool, wet weather conditions of 2017, streams were generally more suitable for trout survival and growth than in 2016 (i.e., warm, dry). All streams were suitable for trout survival in 2017, and most streams (87%, n = 13) had temperatures that were optimal or suitable for summer trout growth (Table 4.3). Only two streams (Paint River, Sturgeon River) were unsuitably warm for summer growth. Based on 2017 conditions, thermal habitats in groundwater-dominated streams were predicted to be suitable for survival of all trout species regardless of MATW/TS_{gw} conditions (Table 4.5, Figure 4.7). Projected groundwater-dominated stream temperatures were suitable for summer growth of rainbow trout in all MATW/TS_{gw} conditions and brook trout and brown trout in all but one condition (MATW = 5.1° C, TS_{gw} = 1; Table 4.3, 4.5, Figure 4.7). Hence, trout will continue to survive and generally maintain summer growth in groundwater-dominated Michigan streams if climate change generates relatively cool, wet future weather conditions.

In cool, wet weather conditions, runoff-dominated streams became less suitable for trout survival and growth as MATW and TS_{pr} increased, but to a lesser extent than in warm, dry conditions (Table 4.4, 4.5, Figure 4.6, 4.7). As MATW increased from +1.7°C to +5.1°C in cool, wet conditions, the mean percentage of runoff-dominated streams suitable for brook trout

TABLE 4.5. Thermal habitat suitability for brook trout (BKT), brown trout (BNT), and rainbow trout (RBT) survival and growth in Michigan streams based 2017 weather conditions (i.e., cool, wet). Table entries report the proportion of streams that are suitable for survival (numerator) and growth (denominator) in three conditions of modeled air temperature warming $(+1.7^{\circ}C, +3.4^{\circ}C, +5.1^{\circ}C)$ and thermal sensitivity of groundwater/precipitation (0.0, 0.66, 0.1; in parentheses). Streams are classified as groundwater-dominated (GD; base flow index > 0.60), runoff-dominated (RD; base flow index < 0.60), or systems with intermediate groundwater input (Int; base flow index = 0.60; Neff et al., 2005).

Species	Stream	+1.7(0)	+1.7(0.66)	+1.7(1)	+3.4(0)	+3.4(0.66)	+3.4(1)	+5.1(0)	+5.1(0.66)	+5.1(1)
BKT	GD (3)	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/0.67
	RD (5)	1/0.8	1/0.6	1/0.6	1/0.6	1/0.6	1/0.6	1/0.6	0.8/0.6	0.6/0.4
	Int (1)	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1
BNT	GD (3)	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/0.67
	RD (6)	1/0.67	1/0.67	1/0.67	1/0.67	1/0.33	1/0.33	1/0.67	1/0.33	0.83/0.33
	Int (2)	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1
RBT	GD (2)	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1
	RD (5)	1/1	1/0.8	1/0.8	1/0.8	1/0.4	0.8/0.4	1/0.8	0.8/0.4	0.4/0.4
	Int (2)	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1

survival and growth declined from 100% (survival) and 67% (growth) to 80% (survival) and 53% (growth). Brown trout exhibited a similar trend, as 100% and 67% of runoff-dominated streams were suitable for survival and growth when MATW = $+1.7^{\circ}$ C, compared to 94% (survival) and 44% (growth) when MATW = $+5.1^{\circ}$ C (Table 4.5, Figure 4.7). Likewise, the mean percentage of runoff-dominated streams suitable for rainbow trout survival and growth decreased from 100% (survival) and 87% (growth) to 73% (survival) and 53% (growth) as MATW increased from $+1.7^{\circ}$ C to $+5.1^{\circ}$ C. Streams with intermediate groundwater input were projected to be suitable for survival and growth of all trout species regardless of MATW/TS_{pr} conditions (Table 4.5, Figure 4.7). Thus, in cool, wet future weather conditions, runoff-dominated streams will exhibit reductions in trout survival and especially growth that are large relative to those in groundwater-dominated streams in similar weather conditions but small relative to those in runoff-dominated streams in warm, dry conditions.

Overall, Michigan coldwater stream temperatures were projected to increase in proportion to the magnitude of air temperature warming and groundwater thermal sensitivity under various climate change scenarios. Stream temperature warming was predicted to be more severe under warm, dry future weather conditions than cool, wet conditions. However, regardless of weather conditions, groundwater-dominated stream temperatures were projected to increase by an appreciably smaller magnitude than runoff-dominated stream temperatures such that brook trout, brown trout, and rainbow trout will continue to survive and generally maintain summer growth in groundwater-dominated streams with continued air temperature warming and increasing groundwater thermal sensitivity, particularly in warm, dry future weather conditions.

Discussion

Michigan coldwater streams vary widely in temperature and thermal habitat suitability for summer trout survival and growth. Whereas runoff-dominated streams are highly sensitive to changes in air temperature, groundwater-dominated streams have thermal regimes that are less affected by air temperature alterations due to groundwater-driven thermal buffering. This indicates a need for a stream temperature modeling approach that accommodates among-stream heterogeneity in thermal drivers (e.g., air temperature, precipitation, groundwater) in an accurate, accessible, management-relevant way. Although heat budget models incorporate a wide array of stream temperature drivers (Leach & Moore, 2011; Westhoff et al., 2011) – including groundwater and precipitation – they are extremely data-intensive, site-restrictive (i.e., only applied in a limited number of streams), expensive to develop, and thus often impractical for fisheries and aquatic resource professionals who seek to efficiently allocate limited fisheries management resources across relatively large areas containing diverse streams and watersheds. Likewise, although air-stream temperature models are inexpensive and readily applicable for climate change forecasting, they overlook hydrological influences on stream temperature including climate-driven changes in precipitation and groundwater (Menberg et al., 2014) – and ignore reach-level variation in stream thermal sensitivity (Tague et al., 2007; Kelleher et al., 2012). Hence, in this study we developed an accurate, cost-effective, management-relevant methodology for predicting effects of changes in air temperature, precipitation, and groundwater on water temperatures in brook trout, brown trout, and rainbow trout streams amid climate change.

Our results indicate that basic modifications to air-stream temperature models greatly improve model fit while incorporating stream-specific effects of groundwater and precipitation

on water temperature. Moreover, models adjusted for ADD and precipitation can be used to project future stream temperatures and trout thermal habitat suitability under varying climate change scenarios (i.e., combinations of MATW and TS_{gw}/TS_{pr}). Importantly, these adjusted models can be applied to hydrologically diverse streams (i.e., both groundwater-dominated and runoff-dominated), thereby expanding the scope of previous research wherein adjusted models were only applied to groundwater-dominated systems (Snyder et al., 2015). As observed herein and in previous research (Westhoff & Paukert, 2014), parity between a stream's hydrological status (groundwater-dominated or runoff-dominated) and its most accurate temperature model (MDAT + ADD or MDAT + precipitation) allows fisheries and aquatic resource professionals and policy makers to use stream hydrology as a criterion to select variables to include in stream temperature models (i.e., MDAT + ADD in groundwater-dominated streams, MDAT + precipitation in runoff-dominated streams). Other researchers have employed network models to accurately predict stream temperatures in the western USA based on thermal spatial autocorrelation driven by elevation gradients and tributary effects (Peterson & Ver Hoef, 2010). However, stream thermal dynamics in Michigan are different from those in western USA streams, as Michigan has relatively little elevation change, larger groundwater influence, more precipitation as rain, and less snowmelt over a shorter annual period. Therefore, stream temperature modeling in the present study required an approach based on groundwater and summer precipitation (i.e., rain). Previous authors have acknowledged the importance of accounting for changes in precipitation patterns in stream climate change modeling (Snyder et al., 2015), but few accurate, cost-effective, management-relevant models that include precipitation have been generated prior to this research. The stream temperature modeling approach developed herein for Michigan streams is readily transferable to other areas where the

primary drivers of stream temperature are air temperature, groundwater, and precipitation (primarily as rain) rather than elevation change or snowmelt.

Signs (i.e., +/-) of the ADD and precipitation coefficients in stream temperature models were consistently negative in 2016 and 2017 in all streams (Table 4.1), indicating thermal buffering effects of both groundwater and precipitation in summer. On average, precipitation coefficients declined by 0.36 from 2016 (mean -0.64) to 2017 (mean -1.00), reflecting cool, wet weather in the latter year (EAWSN, 2018) and demonstrating an overall cooling effect of summer precipitation on stream temperature in runoff-dominated streams. This suggests precipitation, by increasing stream discharge and water volume, can offset effects of increased air temperature on stream temperatures (Merriam et al., 2017). In addition, modeling stream temperatures under divergent weather conditions (i.e., warm/dry, cool/wet) enabled us to generate a diversity of models that encompassed the range of temperature and precipitation conditions that Michigan streams currently experience and are projected to experience in the future. This, in turn, provides fisheries and aquatic resource professionals with a flexible thermal modeling approach for forecasting stream temperatures along a gradient of future temperature and precipitation regimes (Primack, 2000; Parry et al., 2007; Stoner et al., 2013).

Effects of groundwater and precipitation on stream temperatures may be different in the future compared to the present (Kurylyk et al., 2013; Menberg et al., 2014), indicating a need to account for these changes by incorporating stream thermal sensitivity and associated variables (e.g., TS_{gw} , TS_{pr}) into stream temperature modeling. Although stream thermal sensitivity declined with increasing groundwater input, as expected, this relationship was dependent on TS_{gw} conditions. For instance, if groundwater temperature is not affected by warming air temperatures in a changing climate, increased groundwater input will continue to have a

buffering effect on stream temperature (Figure 4.5a). However, more realistically, groundwaterdriven thermal buffering will become weaker or non-existent (Figure 4.5b,c) if TS_{gw} falls between 0.66 and 1.0 as predicted by recent research regarding effects of climate change on groundwater dynamics in coldwater streams (Kurylyk et al., 2013; Snyder et al., 2015). Hence, although groundwater is an important source of cool, oxygen-rich water that trout managers must consider in stream thermal habitat management, groundwater-dominated streams are not static systems that will invariably remain cold in a changing climate.

In addition to groundwater, precipitation affects stream thermal regimes, yet it is rarely accounted for in stream temperature modeling studies (Snyder et al., 2015). This likely reflects the indirect nature and logistical difficulty of measuring mechanisms whereby precipitation influences stream temperature (e.g., changes in timing and magnitude of discharge, turbidity). In the present study, precipitation was projected to have a cooling effect on water temperatures in runoff-dominated Michigan streams via increased stream discharge, as also documented in a West Virginia trout stream (Merriam et al., 2017). Such an important finding would have been masked in the absence of a modeling approach that explicitly accounted for effects of climateinduced changes in precipitation on stream temperature. Hence, precipitation-corrected stream temperature models represent tools that fisheries and aquatic resource professionals can use to reliably forecast effects of changing precipitation regimes on stream trout survival and growth. In turn, they can make corresponding improvements to fisheries management programs and policies and ultimately enhance fisheries sustainability amid climate change. For instance, fisheries managers could use models of current or future precipitation to identify trout streams with precipitation-driven cooling in summer and prioritize them for management activities (e.g., riparian zone protection/rehabilitation to maintain/increase stream shading).

The magnitude of stream warming predicted herein was comparable to previous research in Michigan and surrounding Great Lakes states. Projected stream temperature warming based on the most extreme predicted climatic changes (MATW = 5.1° C, TS_{gw}/TS_{pr} = 1.0) was 0.7– 7.0°C for warm, dry weather conditions and 0.9–5.7°C for cool, wet conditions. These ranges are similar to those documented in studies in Michigan (0.1–6.8°C; Carlson et al., 2017), Wisconsin (0.8–4.0°C; Lyons et al., 2010), and Minnesota (0.3–6.9°C; Pilgrim et al., 1998). However, in the present study, explicit consideration of hydrological alterations driven by climate change drivers increased the reliability of stream temperature projections relative to previous research. For example, stream temperatures were predicted to increase by 0.1-3.8°C in groundwaterdominated Michigan streams and 0.2–6.8°C in runoff-dominated streams by Carlson et al. (2017). However, probable changes in thermal sensitivity of groundwater and precipitation were not accounted for in prior Michigan studies, so projected warming reported herein for groundwater-dominated streams (2.4-4.5°C [warm, dry]; 2.9-4.6°C [cool, wet]) and runoffdominated systems (3.3–7.0°C [warm, dry]; 2.7–5.7°C [cool, wet]) is likely more reliable and thus of greater assistance to fisheries managers for trout thermal habitat management. Overall, this study corroborates the observation that groundwater-dominated streams are more thermally resilient than runoff-dominated streams and thus offer better growing conditions for trout during warm summer months (Zorn et al., 2012) and other thermally stressful times of year. These findings suggest that groundwater conservation efforts (e.g., protecting groundwater recharge by conserving grasslands and restricting groundwater withdrawal; Waco & Taylor, 2010) should be a key component of coldwater stream fisheries management programs in Michigan and elsewhere.

Results of this study indicate that current climate change drivers will likely increase Michigan stream temperatures and degrade thermal habitats for summer trout survival and growth, with the extent of degradation dependent on the magnitude of air temperature warming and changes in groundwater input and precipitation patterns. Overall, groundwater-dominated streams were predicted to be more thermally resilient than runoff-dominated streams, yet the thermal buffering capacity of groundwater was appreciably lower when $TS_{gw} = 0.66$ or 1.0, both of which are more realistic than $TS_{gw} = 0.0$ (Kurylyk et al., 2013; Snyder et al., 2015). Nevertheless, all groundwater-dominated streams studied herein were projected to remain suitable for survival of brook trout, brown trout, and rainbow trout regardless of climate change conditions (i.e., MATW, TS_{gw}/TS_{pr}) and baseline weather (i.e., warm/dry, cool/wet). Projected summer trout survival and growth were lower in runoff-dominated streams than groundwaterdominated streams and declined progressively as climatic changes intensified (i.e., MATW = $+3.4^{\circ}$ C or 5.1° C, TS_{gw}/TS_{pr} = 0.66 or 1.0). Rainbow trout were relatively more resistant to reductions in summer growth compared to brook trout and especially brown trout because they can grow in a moderately wider temperature range than the latter species (Wurtsbaugh and Davis 1977). Although the greatest declines in trout survival and growth were predicted in runoffdominated streams in warm, dry weather conditions, survival and growth were still affected in cool, wet conditions. Therefore, resource managers should prioritize trout management in runoffdominated streams capable of thermal habitat rehabilitation – particularly those predicted to experience increased precipitation and an associated cooling effect - and in groundwaterdominated streams where management activities produce tangible returns on investment relative to trout survival and growth. For example, it would be inefficient to expend resources (e.g., money, time, personnel) in runoff-dominated streams that exceed trout temperature tolerances or, alternatively, groundwater-dominated streams that can sustain their thermal habitat conditions independent of human intervention (e.g., cold streams such as the East Branch Fox River).

Projected declines in thermal habitat suitability for summer trout growth - and, to a lesser extent, survival – will likely be manifested by changes in thermal habitat availability and connectivity. For instance, reduced overall availability of thermal habitats suitable for trout growth will likely make it more difficult for fish to move to cold habitats, with possible effects on trout population distribution in Michigan (Carlson et al., 2016), where dam-induced habitat fragmentation is already extensive (Cooper et al. 2016). By isolating coldwater habitats in particular locations (e.g., headwaters), climate change could subdivide stream trout populations and further reduce survival (Steen et al., 2010). For instance, in Wisconsin, USA, the length of streams suitable for brook trout was projected to decline by 44%, 94%, and 100% under climate change classified as limited (summer air temperatures increase 1.0° C and water 0.8° C), moderate (air +3.0°C, water +2.4°C), and major (air +5.0 °C, water +4.0 °C; Lyons et al., 2010). Although annual (as opposed to summer) trout growth could stabilize or increase in a changing climate due to a lengthened growing season (and perhaps greater availability of warmwater prey), fisheries and aquatic resource professionals should account for predicted reductions in trout survival and growth during the warmest period of the year as they develop management programs to increase trout sustainability.

Results of this study have important implications and applications for trout management within and beyond Michigan. Managing coldwater streams and their thermally sensitive fish populations for thermal resilience (i.e., ability to absorb temperature changes and retain ecosystem structure and function; Holling, 1973) will be increasingly important as climate change continues to degrade coldwater habitats throughout the world (Almodóvar et al., 2012;

Isaak et al., 2012; Santiago et al., 2015). Amid limitations in money, time, personnel, and other resources for fisheries management, fisheries and aquatic resource professionals will benefit from accurate, cost-effective, management-relevant stream temperature models such as those described herein. In turn, lower resource expenditure on temperature data collection and model development will allow greater resource allocation toward thermal habitat management activities. For instance, resource managers can form public–private partnerships to protect key groundwater resources (e.g., springs, seeps); conserve grasslands and other watershed-level vegetation and soil types that promote groundwater recharge; preserve and rehabilitate riparian trees and plants that promote water infiltration, percolation, and stream shading; and sustain longitudinal stream connectivity to allow trout movement to coldwater habitats during summer (Waco & Taylor, 2010; Siitari et al., 2011).

Collectively, these and related strategies can be used to develop resilience-based management programs for coldwater streams and their important trout fisheries (Carlson et al., 2016). Resilience-based management involves collaboration among scientists, biologists, policy makers, and public stakeholders to cultivate fisheries ecosystems that are robust to local and global change (e.g., climate change, land use alteration) and, likewise, management systems that can withstand environmental and socioeconomic stressors (Paukert et al., 2016). For example, resource managers can increase the resilience of fisheries ecosystems by protecting a diversity of trout age and size classes and prey resources that tolerate a wide range of temperatures expected in a changing climate (Hansen et al., 2015), instituting angling regulations (e.g., reduced creel limits, protected slot limits) that preserve trout populations during thermally stressful times, and monitoring precipitation levels and associated thermal effects in runoff-dominated streams. Similarly, resource managers can enhance management system resilience by developing public

outreach programs that inform stakeholders about thermal habitat management, prepare them for realistic stream fish community outcomes amid climate change (e.g., salmonid decline, centrarchid expansion; Pease & Paukert, 2014), and garner their support for resilience-based salmonid management.

In conclusion, we developed a methodology for, and demonstrated the advantages of, modeling effects of air temperature, groundwater input, and precipitation patterns on stream thermal regimes in an accurate, cost-effective, management-relevant manner. The modeling approach described herein allows fisheries and aquatic resource professionals to forecast and respond to effects of climate change on populations of trout and other fish species in management-relevant ways. Methods used in this study are widely applicable throughout the range of brook trout, brown trout, and rainbow trout (and other species) because they only require readily available (or easily collectable) air/stream temperature and precipitation data and readily accommodate other thermal drivers (e.g., riparian/watershed land cover). This stream temperature modeling approach is also flexible because it can be applied in streams with diverse air temperature and hydrological regimes (i.e., groundwater-dominated and runoff-dominated systems), thereby expanding the scope of previously developed groundwater models (Snyder et al., 2015) and helping fill knowledge gaps regarding the effects of precipitation changes (e.g., thermal sensitivity, magnitude, timing) on stream temperature. Overall, precipitation- and groundwater-corrected stream temperature models are useful for reliable thermal forecasting and associated management efforts ranging from groundwater conservation to riparian habitat rehabilitation and public engagement. In turn, these activities will promote sustainable, resilience-based management of coldwater streams and their socio-ecologically important trout fisheries within and beyond Michigan in a changing climate.

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APPENDIX

TABLE 4.6 (Appendix 4.1). Mean daily water temperatures in Michigan trout streams from late-May to late-October 2018. Abbreviations are as follows: AUS = Au Sable River, BLK = Black River, CED = Cedar River (Upper Peninsula), EBF = East Branch Fox River, MAN = Manistee River, PAN = Paint River, PIG = Pigeon River, PIN = Pine River (Southern Lower Peninsula), STJ = St. Joseph River, STU = Sturgeon River (Upper Peninsula), TAM = Tamarack River.

Date	AUS	BLK	CED	EBF	MAN	PAN	PIG	PIN	STJ	STU	TAM
5/26/2018	N/A	17.93	20.59	N/A	18.47						
5/27/2018	N/A	18.10	21.36	N/A	18.71						
5/28/2018	N/A	18.28	22.55	N/A	18.53						
5/29/2018	N/A	18.75	23.11	N/A	19.29						
5/30/2018	N/A	18.26	22.66	N/A	18.48						
5/31/2018	N/A	19.03	22.45	N/A	20.10						
6/1/2018	N/A	18.25	22.30	N/A	19.00						
6/2/2018	15.87	13.06	N/A	N/A	15.03	N/A	11.57	16.21	20.87	N/A	16.35
6/3/2018	14.48	11.95	N/A	N/A	13.27	N/A	10.66	14.89	19.49	N/A	14.90
6/4/2018	14.76	12.49	N/A	N/A	14.39	N/A	11.22	14.92	19.34	N/A	15.63
6/5/2018	13.22	11.14	N/A	N/A	12.88	N/A	10.02	14.74	18.93	N/A	15.48
6/6/2018	13.24	11.67	N/A	N/A	13.26	N/A	10.42	13.67	18.19	N/A	14.80
6/7/2018	14.88	12.97	N/A	N/A	14.95	N/A	11.32	15.07	19.26	N/A	16.53
6/8/2018	15.37	13.21	N/A	N/A	15.12	N/A	11.49	16.10	19.90	N/A	17.35
6/9/2018	15.36	13.53	N/A	N/A	15.24	N/A	11.71	14.98	19.25	N/A	15.09
6/10/2018	15.44	13.62	N/A	N/A	14.74	N/A	11.68	14.35	18.20	N/A	14.36
6/11/2018	15.54	13.36	N/A	N/A	15.19	N/A	11.59	14.89	17.85	N/A	16.11
6/12/2018	16.26	14.16	N/A	N/A	16.21	N/A	12.12	15.68	18.17	N/A	17.50
6/13/2018	16.94	14.77	N/A	N/A	16.63	N/A	12.47	16.98	19.19	N/A	18.58
6/14/2018	16.23	14.24	N/A	N/A	15.78	N/A	12.26	16.01	19.48	N/A	17.40
6/15/2018	14.64	13.20	N/A	N/A	14.22	N/A	11.35	15.12	19.97	N/A	16.29
6/16/2018	15.27	13.69	N/A	N/A	14.43	N/A	11.67	15.56	20.19	N/A	16.22
6/17/2018	17.34	15.35	N/A	N/A	16.67	23.07	13.11	17.21	21.42	N/A	18.83
6/18/2018	17.65	15.54	17.38	13.88	16.92	22.77	13.09	18.56	23.25	22.18	19.98
6/19/2018	16.25	13.86	16.51	13.24	15.12	22.64	12.22	16.85	22.19	22.40	17.08
6/20/2018	16.96	14.28	16.27	13.16	16.27	22.72	12.54	15.73	19.40	22.90	16.25
6/21/2018	16.61	14.37	15.92	13.18	16.06	22.49	12.45	15.74	18.65	23.10	17.10
6/22/2018	14.99	12.61	14.70	12.54	14.68	22.15	11.27	15.01	18.28	23.21	15.87
6/23/2018	14.02	12.01	14.50	12.51	13.54	22.64	10.95	14.85	18.27	23.68	15.38
6/24/2018	15.50	12.58	14.35	12.35	15.37	22.74	11.73	15.25	18.97	21.82	15.70
6/25/2018	15.88	13.06	14.32	11.69	15.72	21.84	11.84	15.68	19.66	21.40	17.35
6/26/2018	15.23	13.00	14.72	12.08	15.21	21.57	11.63	14.69	19.77	22.02	16.57
6/27/2018	15.60	14.03	17.41	12.79	15.72	22.50	12.21	15.69	19.52	23.56	16.92
6/28/2018	17.26	15.15	18.98	13.65	17.06	24.10	13.04	16.65	20.28	25.17	18.07

TABLE 4.6 (Appendix 4.1) (cont'd).

Date	AUS	BLK	CED	EBF	MAN	PAN	PIG	PIN	STJ	STU	TAM
6/29/2018	18.15	15.97	20.90	14.03	17.94	24.59	13.56	17.94	22.02	25.81	19.92
6/30/2018	20.57	18.53	20.90	14.43	20.51	26.61	15.23	19.70	21.71	26.73	21.94
7/1/2018	20.86	19.01	20.48	14.37	20.31	25.77	15.46	20.27	21.71	26.19	22.27
7/2/2018	19.89	19.01	19.17	14.30	19.33	24.68	14.87	19.52	21.30	25.66	21.44
7/3/2018	18.98	17.20	20.10	14.23	19.55	25.31	14.31	19.32	20.99	26.44	20.67
7/4/2018	19.19	17.70	19.33	14.33	18.61	25.26	14.65	19.04	21.55	26.89	22.13
7/5/2018	19.76	17.65	19.80	14.78	18.86	25.70	15.12	19.79	21.33	27.21	22.13
7/6/2018	17.75	15.69	16.45	13.21	16.98	24.98	13.75	18.05	20.35	25.34	20.63
7/7/2018	16.80	15.00	16.93	12.89	16.50	25.16	13.23	16.19	19.52	25.22	19.37
7/8/2018	17.18	15.58	18.53	13.54	16.93	25.45	13.48	16.25	19.91	24.94	19.53
7/9/2018	17.82	16.19	20.56	13.80	17.47	26.34	13.87	17.26	20.32	25.92	19.93
7/10/2018	17.98	15.87	17.72	13.02	17.36	26.20	13.68	18.05	21.01	25.43	20.74
7/11/2018	17.02	15.25	16.78	12.69	16.70	25.08	13.25	16.91	20.42	24.97	20.31
7/12/2018	15.38	14.14	16.99	12.35	15.02	23.72	12.46	16.15	20.22	24.19	19.37
7/13/2018	17.36	15.60	18.03	13.01	17.26	24.09	13.73	17.68	20.92	24.58	20.67
7/14/2018	17.98	15.80	19.38	13.44	17.76	24.95	13.86	17.43	20.75	26.15	20.27
7/15/2018	18.36	16.35	19.88	14.04	18.35	25.82	14.10	17.59	21.21	26.71	19.79
7/16/2018	18.51	16.29	21.05	14.29	17.49	26.10	14.09	18.26	20.87	26.68	21.20
7/17/2018	16.64	14.74	15.82	12.98	15.97	24.54	13.33	16.78	20.41	23.74	19.37
7/18/2018	15.81	14.20	14.52	11.77	15.38	24.15	12.79	15.77	19.78	23.32	18.51
7/19/2018	16.11	14.56	16.75	12.72	15.87	23.81	12.82	15.60	19.95	24.10	18.54
7/20/2018	16.21	14.95	18.28	12.96	16.33	22.61	13.12	16.29	19.82	24.27	18.72
7/21/2018	15.96	14.41	17.02	13.10	15.79	21.27	13.39	16.26	19.86	22.96	18.15
7/22/2018	16.69	15.29	17.87	13.71	16.82	21.48	14.27	16.35	19.89	22.16	17.45
7/23/2018	16.56	14.41	18.43	12.97	16.29	22.88	13.28	15.72	19.75	22.49	17.00
7/24/2018	16.80	14.72	18.60	13.36	17.02	23.92	13.54	16.10	20.29	23.70	17.15
7/25/2018	17.15	14.81	17.48	13.27	17.12	23.41	13.52	16.64	20.30	23.59	18.46
7/26/2018	16.95	14.92	15.97	13.22	16.96	21.96	13.51	16.77	19.96	22.55	18.91
7/27/2018	15.91	13.61	15.00	12.12	15.41	20.56	12.75	15.57	19.57	20.88	17.62
7/28/2018	16.03	13.85	15.08	11.97	15.70	20.71	12.94	15.30	19.31	21.18	17.13
7/29/2018	15.33	13.64	15.68	12.25	15.52	22.26	12.82	15.42	19.52	22.14	17.91
7/30/2018	15.38	14.00	16.25	12.26	15.68	23.19	12.90	15.51	19.57	23.28	18.51
7/31/2018	16.10	14.19	17.31	12.75	15.61	23.64	12.97	15.54	19.48	23.76	18.64
8/1/2018	16.40	14.48	15.94	13.13	15.62	23.32	13.08	16.20	19.80	23.61	18.77
8/2/2018	16.06	14.09	13.57	12.38	15.39	20.91	13.03	16.34	20.09	21.44	18.78
8/3/2018	17.09	14.23	16.19	11.95	16.57	20.64	13.19	16.96	20.19	21.51	19.54
8/4/2018	17.35	14.42	16.21	12.34	16.56	20.89	13.38	16.71	20.52	22.44	19.96
8/5/2018	18.99	16.74	17.47	12.79	18.68	22.06	14.50	18.14	21.21	22.80	21.15

TABLE 4.6 (Appendix 4.1) (cont'd).

Date	AUS	BLK	CED	EBF	MAN	PAN	PIG	PIN	STJ	STU	TAM
8/6/2018	17.43	15.68	17.96	12.74	16.69	23.72	13.97	17.63	20.66	23.47	20.23
8/7/2018	17.26	14.94	17.19	12.79	16.56	23.57	13.56	17.04	20.52	23.04	18.85
8/8/2018	17.33	14.75	17.51	12.19	16.46	23.99	13.32	17.45	20.37	23.34	19.64
8/9/2018	16.90	15.26	18.32	13.28	16.88	24.86	13.63	17.31	19.96	24.44	20.11
8/10/2018	16.55	14.73	17.65	12.61	16.35	24.99	13.36	17.13	20.49	24.43	20.64
8/11/2018	16.96	14.91	18.57	12.94	17.01	25.38	13.54	16.57	20.40	25.01	20.15
8/12/2018	16.64	14.78	17.97	12.64	16.63	25.48	13.42	16.76	20.47	25.16	20.46
8/13/2018	16.81	14.63	18.82	12.76	16.66	25.77	13.26	17.07	20.39	25.41	20.47
8/14/2018	16.80	15.11	19.21	12.97	16.95	26.08	13.70	17.03	20.32	25.63	20.20
8/15/2018	16.95	15.39	18.57	13.00	16.70	25.09	13.68	17.23	20.47	24.44	20.47
8/16/2018	17.00	15.06	18.48	12.83	16.76	24.53	13.63	16.87	20.22	24.71	20.42
8/17/2018	17.06	15.08	19.21	12.93	16.50	24.29	13.56	16.14	20.09	24.54	18.98
8/18/2018	16.37	14.36	17.69	12.68	15.98	24.28	13.34	16.15	20.54	23.45	17.88
8/19/2018	16.82	14.23	16.33	11.71	16.19	23.57	13.20	16.73	20.15	23.01	19.22
8/20/2018	16.12	14.44	17.37	11.87	15.83	22.89	13.22	16.67	19.86	23.31	19.30
8/21/2018	14.98	13.33	16.47	11.82	14.46	21.70	12.72	17.27	20.17	21.31	18.73
8/22/2018	15.34	13.65	15.02	11.42	15.22	20.42	13.14	16.58	19.39	20.45	17.90
8/23/2018	14.80	13.57	16.01	11.35	14.81	20.82	12.87	15.37	19.19	21.05	17.53
8/24/2018	14.43	13.86	14.90	11.78	14.51	20.51	12.54	15.06	19.20	20.58	17.33
8/25/2018	14.29	13.89	16.10	11.64	14.21	20.63	12.80	15.83	20.08	20.69	17.32
8/26/2018	16.18	14.44	16.53	11.76	15.79	21.02	13.35	16.90	20.86	21.19	18.69
8/27/2018	16.44	14.62	18.47	12.45	15.98	21.61	13.44	19.00	21.42	22.21	20.08
8/28/2018	17.50	15.61	17.81	12.93	16.76	21.35	14.45	19.90	21.13	21.67	20.92
8/29/2018	17.14	15.27	15.68	11.95	16.14	19.69	14.32	19.44	20.24	19.53	19.78
8/30/2018	14.99	13.41	13.49	10.59	14.24	18.58	12.52	16.50	19.05	18.68	17.02
8/31/2018	14.56	13.16	14.64	10.86	14.42	18.68	12.49	15.88	19.67	18.67	17.17
9/1/2018	15.35	14.27	17.81	11.93	15.11	20.27	13.03	16.60	20.70	19.93	17.24
9/2/2018	16.62	14.69	17.97	12.40	16.05	21.49	13.58	17.73	21.11	20.84	19.05
9/3/2018	17.41	15.18	17.75	12.18	16.64	21.60	13.90	19.66	20.69	21.62	20.11
9/4/2018	17.80	15.58	17.18	12.07	16.92	21.66	14.76	20.08	21.03	21.46	20.57
9/5/2018	18.28	16.62	17.81	15.18	17.00	21.27	14.76	20.47	21.25	20.97	20.43
9/6/2018	16.71	15.54	15.62	13.56	15.74	20.06	13.46	18.89	19.81	20.08	18.77
9/7/2018	14.21	12.41	13.92	11.53	13.40	19.64	11.74	16.00	19.22	19.84	15.85
9/8/2018	13.41	11.77	13.22	11.33	13.09	18.82	11.51	14.94	18.69	19.08	15.06
9/9/2018	12.58	10.90	12.28	10.31	12.53	18.06	10.85	13.92	18.20	18.76	14.46
9/10/2018	12.70	10.97	11.82	10.13	12.76	18.10	10.89	13.99	18.42	18.69	14.99
9/11/2018	13.69	12.02	13.23	10.82	13.70	19.15	11.62	14.34	18.77	19.23	15.50
9/12/2018	14.31	13.10	15.32	11.55	14.15	19.77	12.09	14.35	18.78	20.27	16.13

TABLE 4.6 (Appendix 4.1) (cont'd).

Doto	AUS	BLK	CED	EBF	MAN	PAN	PIG	PIN	STJ	STU	TAM
Date 9/13/2018	14.54	13.01	15.75	11.66	14.25	20.19	12.16	14.38	19.38	20.79	16.18
9/13/2018	14.54	13.93	15.85	11.00	14.23	20.19	12.10	14.38	20.00	20.79	16.83
9/14/2018	15.22	13.44	13.85	12.31	13.33	20.99	12.64	14.74	20.00 19.94	21.47	16.58
	15.22		18.30	12.31				15.05	20.34	22.28	10.58
9/16/2018 9/17/2018		13.75		12.44	15.10 15.49	22.16	12.78		20.54	22.90	
	15.63 15.31	14.82 13.92	18.06			22.25	13.27	15.19			18.26
9/18/2018			12.55	11.25	14.92	20.59	12.80	15.41	20.38	19.64	17.68
9/19/2018	13.65	12.69	11.49	10.49	13.19	18.82	11.92	15.21	19.90	18.54	16.21
9/20/2018	13.23	12.34	14.13	10.73	12.78	17.67	11.92	14.91	20.33	18.28	16.43
9/21/2018	14.59	13.88	15.10	11.68	14.39	16.75	12.97	15.15	20.34	17.98	17.86
9/22/2018	12.16	11.10	11.59	9.43	11.71	15.04	10.82	14.75	17.76	15.85	14.39
9/23/2018	11.49	10.57	11.47	9.97	11.34	14.84	10.62	13.62	17.98	16.21	13.70
9/24/2018	12.62	11.78	13.21	10.06	12.75	14.97	11.46	13.39	18.42	16.30	14.52
9/25/2018	14.39	13.38	13.99	10.40	14.54	15.36	12.49	13.84	20.04	16.16	16.84
9/26/2018	12.99	12.01	11.98	9.61	12.68	14.12	11.67	14.34	18.54	14.91	15.93
9/27/2018	11.19	10.51	10.23	8.40	10.99	13.17	10.54	13.59	17.31	13.78	13.07
9/28/2018	11.10	10.82	10.42	8.96	11.18	12.21	10.69	13.24	17.85	13.47	13.23
9/29/2018	9.76	9.54	8.44	7.98	9.60	10.64	9.67	12.67	17.33	12.03	11.31
9/30/2018	9.13	8.91	7.87	7.51	9.06	10.28	9.19	11.96	18.17	11.50	10.65
10/1/2018	9.18	9.14	8.23	7.82	9.49	10.21	9.42	10.84	18.70	11.25	10.53
10/2/2018	9.81	9.81	9.38	8.25	9.93	10.14	9.84	11.48	19.12	11.69	11.85
10/3/2018	10.59	10.55	11.03	9.03	10.62	10.67	10.38	13.03	19.80	12.34	14.16
10/4/2018	11.93	12.22	11.50	10.08	12.00	10.83	11.43	14.61	19.72	11.90	15.65
10/5/2018	8.70	8.73	8.34	7.73	8.45	9.60	8.86	10.67	17.34	10.46	10.92
10/6/2018	9.90	9.79	8.92	8.46	9.74	9.33	9.78	12.03	19.33	10.84	12.86
10/7/2018	9.58	9.45	8.61	8.19	9.18	8.91	9.50	11.97	18.57	10.05	12.44
10/8/2018	10.38	10.32	9.03	8.15	10.36	8.83	10.15	12.47	19.03	10.03	13.52
10/9/2018	12.96	12.92	9.82	9.09	13.00	9.01	11.73	14.48	N/A	10.16	15.81
10/10/2018	13.73	13.35	9.16	9.16	13.31	8.50	11.99	15.39	N/A	9.83	15.97
10/11/2018	12.35	12.03	8.97	9.57	11.47	8.00	10.99 8 62	14.12	N/A	10.03	13.99
10/12/2018	8.40	8.60	6.47 5.10	7.60	8.02	6.03	8.62	10.12	N/A	8.56	10.40
10/13/2018	8.01 8.25	7.88 8.26	5.10	6.95 7.42	7.86 8.27	4.92	8.17	8.70	N/A	7.97	9.15 N/A
10/14/2018	8.35	8.36	5.95	7.43	8.27	5.09	8.66	N/A	N/A	7.83	N/A
10/15/2018	8.18	8.31	4.72	6.36	7.91 7.28	4.33	8.36 7 7 8	N/A	N/A	6.96	N/A
10/16/2018	7.26	7.31	4.59 4.68	6.16 5.01	7.38	3.87	7.78	N/A N/A	N/A	6.57 5.88	N/A
10/17/2018	6.95	6.96	4.68	5.91	7.07	3.67	7.38	N/A	N/A	5.88 5.41	N/A
10/18/2018	6.16	6.15 7.41	3.40 5.17	5.32	6.43 7.26	3.60	6.90 7.08	N/A	N/A	5.41 5.07	N/A
10/19/2018	7.07	7.41	5.17	6.26	7.26	5.00	7.98	N/A N/A	N/A	5.97 5.45	N/A
10/20/2018	6.89	7.21	5.02	6.23	6.90	4.61	7.60	N/A	N/A	5.45	N/A

Date	AUS	BLK	CED	EBF	MAN	PAN	PIG	PIN	STJ	STU	TAM
10/21/2018	5.74	5.96	3.99	5.47	5.61	3.77	6.78	N/A	N/A	4.64	N/A
10/22/2018	5.83	6.12	3.43	5.14	6.15	3.91	6.72	N/A	N/A	4.76	N/A
10/23/2018	6.56	6.64	4.52	6.15	6.75	4.66	7.26	N/A	N/A	5.34	N/A
10/24/2018	6.54	6.31	4.20	5.82	6.63	4.74	7.10	N/A	N/A	5.12	N/A
10/25/2018	5.11	5.07	4.03	5.09	4.91	5.28	6.01	N/A	N/A	4.51	N/A
10/26/2018	N/A	N/A	5.05	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

TABLE 4.6 (Appendix 4.1) (cont'd).

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SYNTHESIS

A changing climate will directly and indirectly affect Michigan's coldwater streams and their trout populations (Chapter 1). However, these effects will likely vary according to streamspecific groundwater regimes, precipitation patterns, and riparian and watershed land cover. I found that thermal habitats in groundwater-dominated streams (baseflow index > 0.60; McKergow et al. 2005; Dukić and Mihailović 2012) can be accurately modeled and effectively managed using a generalized (i.e., region-specific) approach that encompasses regional groundwater dynamics. However, in surface runoff-dominated systems (BFI ≤ 0.60) where groundwater is not a primary hydrological driver, a more resource-intensive stream-specific approach is needed, particularly in streams containing high-priority fisheries resources (e.g., trophy individuals, endangered species; Chapter 2). Regardless of stream hydrology, decisionsupport tools – information systems that organizations and individuals use to make science-based fisheries management decisions – facilitate trout management decision-making by systematically integrating thermal, hydrological, and biological (i.e., fish abundance and species composition) information about trout streams across local and regional scales (Carlson et al. 2018). For instance, I developed a decision-support tool that synthesizes fisheries manager-defined decision-making criteria (e.g., current and future stream temperature, trout abundance, groundwater input) and thereby enables fisheries professionals to prioritize streams according to their importance for trout management (Chapter 3). Ultimately, decision-support tools promote resilience-based salmonid management by integrating thermal, hydrological, and biological factors in streams and forecasting future biotic and abiotic conditions, allowing fisheries professionals to make informed decisions to increase stream thermal resilience and socialecological resilience (e.g., groundwater conservation, riparian habitat protection/rehabilitation, public outreach efforts). Likewise, precipitation- and groundwater-corrected stream temperature

models provide an effective method to accurately forecast future thermal habitat conditions for trout growth and survival, enabling fisheries professionals to enhance the thermal resilience of trout streams and the social-ecological resilience of trout management programs. For instance, fisheries professionals can promote resilience-based salmonid management by forming public– private partnerships to rehabilitate riparian vegetation and associated shading (Blann et al. 2002), protect watershed land cover types with high groundwater recharge (e.g., grasslands; Waco & Taylor 2010; Siitari et al. 2011), and inform fisheries stakeholders about realistic expectations for stream fisheries amid climate change (e.g., salmonid decline, centrarchid expansion; Pease & Paukert 2014).

Climate change will affect Michigan stream trout

As coldwater fishes with limited tolerance of warm water conditions, stream salmonids are particularly susceptible to short- and long-term changes in climate that increase stream temperatures (Thomas et al. 2015). In particular, trout growth, reproduction, and survival are regulated by temperature and thus are likely to be affected by warming stream thermal regimes in a changing climate. Hence, it is important for fisheries professionals to predict how trout will be affected by warming air and water temperatures and other climatic changes (e.g., more variable and intense precipitation, increased groundwater temperature and reduced inflow; Parry et al. 2007; Stoner et al. 2013; Menberg et al. 2014) and use this information to establish resilience-based salmonid management programs. As such, I measured water temperatures in a representative sample of coldwater streams throughout Michigan and developed stream-specific temperature models to forecast thermal habitat suitability in a changing climate from 2006 to 2056 (Chapter 1). For this study, I selected 30 trout streams throughout Michigan to represent the variability in air and water temperatures, hydrological conditions (i.e., groundwater to surface runoff dominance), and trout species composition (i.e., combinations of Brook Trout, Brown Trout, and Rainbow Trout) experienced by Michigan stream trout. Stream temperatures were projected to increase between 0.19 and 5.94 °C by 2056 due to predicted air temperature warming, with reduction in growth and survival of Brook Trout, Brown Trout, and Rainbow Trout (Chapter 1). Thermal habitat impairment for growth was predicted to occur least frequently in Rainbow Trout streams as this species has a wider temperature range for growth (12.0–22.5 °C) compared to Brook Trout (11.0–20.5 °C) and Brown Trout (12.0–20.0 °C; Wurtsbaugh & Davis 1977). Overall, projected increases in Michigan stream temperatures will result in thermal habitat conditions less conducive for trout growth and survival during the warmest period of the year, particularly in surface runoff-dominated streams with minimal groundwater-driven thermal buffering capacity, suggesting a need for resilience-based salmonid management (explored further below).

Stream hydrology influences the effectiveness of thermal habitat modeling approaches

Despite the utility of stream-specific regression models for projecting future stream temperatures with high accuracy (i.e., exactness of temperature prediction; Chapter 1), streamspecific models are resource-intensive in terms of the time, money, and personnel required for data collection, management, and modeling. As such, I compared stream-specific and generalized (i.e., region-specific) temperature models in Michigan trout streams to evaluate the potential tradeoff between model accuracy and efficiency (i.e. applicability at managementrelevant spatial extents; Chapter 2). For this study, I selected 52 streams throughout Michigan that represented the thermal, hydrological, and biological (i.e., fish abundance and species

composition) conditions experienced by Michigan stream trout. Generalized models were less accurate than stream-specific models in projecting stream temperatures, particularly in runoffdominated streams, where they had 54% overall accuracy. However, generalized models accurately predicted thermal habitat suitability (82% overall accuracy) in groundwaterdominated streams containing Brook Trout (80% accuracy), Brown Trout (89% accuracy), and Rainbow Trout (75% accuracy; Chapter 2). Hence, amid climate change and constraints in resource availability, fisheries professionals can use generalized models to forecast thermal conditions in groundwater-dominated streams, reserving resource-intensive stream-specific models for surface runoff-dominated systems containing high-priority fisheries resources (e.g. trophy individuals, endangered species).

Decision-support tools help integrate climate change predictions into trout management

Fisheries professionals face the difficult task of synthesizing diverse types of information (e.g., thermal, hydrological, biological) to make effective trout management decisions. To help facilitate this data integration process, I collaborated with fisheries professionals from the MDNR and the USGS to produce a decision-support tool for stream trout management within and beyond Michigan in a changing climate (Chapter 3). The tool ranked trout streams by their management priority based on manager-defined decision-making criteria, including current and projected 2056 stream temperature, groundwater input, trout relative abundance, and watershed and riparian land cover. The decision-support tool highlighted a spectrum of stream trout fisheries, ranging from recreationally significant systems whose future warming is likely to reduce the importance of trout fisheries (e.g., Muskegon River) to lesser-known streams projected to become more thermally suitable for trout and thus significant for trout management

(e.g., Davenport Creek; Chapter 3). Overall, the decision-support tool promotes resilience-based salmonid management by providing fisheries professionals with a knowledge base to integrate diverse data (e.g., biological, hydrological, thermal) and forecast future stream conditions within and beyond Michigan, ultimately ranking streams according to their priority for management interventions to increase thermal and social-ecological resilience (e.g., groundwater conservation, riparian habitat protection/rehabilitation, public outreach efforts).

Monitoring and modeling precipitation and groundwater are critical for resilience-based salmonid management

Incorporating precipitation and groundwater dynamics (e.g., amount, temperature) into stream temperature monitoring and modeling programs is important for resilience-based salmonid management in a changing climate because these factors have significant effects on stream thermal regimes. However, precipitation and groundwater are rarely included together in stream temperature models. Until recently, stream temperature models have largely ignored variability in precipitation and groundwater dynamics (e.g., magnitude, timing, temperature) among streams and stream reaches (Snyder et al. 2015). This inhibits the accuracy of stream temperature forecasting and thus the efficacy of trout management in a changing climate. To help fill this knowledge gap, I developed an approach for predicting the effects of changes in air temperature, precipitation, and groundwater on coldwater stream temperatures and Brook Trout, Brown Trout, and Rainbow Trout growth and survival in Michigan (Chapter 4). Precipitationand groundwater-corrected stream temperature models (mean $R^2 = 0.83$) were more accurate than conventional air-stream temperature models (mean $R^2 = 0.58$) in predicting stream temperatures to the year 2056. Projected stream warming intensified in proportion to simulated

air temperature warming and was most extreme in surface runoff-dominated streams, given their limited groundwater-driven thermal buffering (Carlson et al. *in review*, Chapter 4). However, groundwater-dominated streams will not invariably provide coldwater habitats needed by Brook Trout, Brown Trout, and Rainbow Trout if groundwater temperatures increase or groundwater inputs decline due to reduced precipitation or groundwater withdrawal by humans for other activities (e.g., irrigation, municipal use). Fisheries professionals throughout Michigan, the United States, and the world can use precipitation- and groundwater-corrected stream temperature models to better forecast effects of climate change on trout growth and survival and ultimately develop resilience-based salmonid management programs, thereby enhancing the sustainability of trout fisheries now and in the years to come. LITERATURE CITED

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